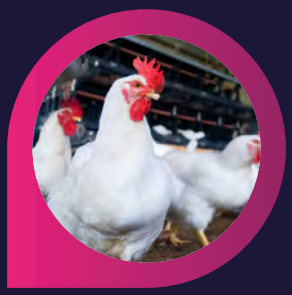
PRECISION LIVESTOCK FARMING '19


Edited by: B. O'Brien, D. Hennessy and L. Shalloo

PRECISION LIVESTOCK FARMING '19

Precision Livestock Farming '19

Papers presented at the
9th European Conference on Precision Livestock Farming
Cork, Ireland
26-29 August '19

Edited by:

B. O'Brien
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The 9th European Conference on Precision Livestock Farming

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Editorial

We would like to welcome all delegates of the 9th European Precision Livestock Conference to Cork, Ireland.

From both business and societal viewpoints, when we consider livestock farming, we need to focus on economic performance, environmental impact, well-being of the livestock unit and of the manager to ensure the sustainability of farm and food production into the future, and also the consumer. Never before have all of these aspects of livestock production been challenged on so many levels. Precision technologies can help farmers to become more effective and help the consumer to source products that satisfy all of these requirements. Precision Livestock Farming (PLF) focuses on using technology to monitor and collect livestock data on a continuous and automated basis, with the ultimate goal of providing a mechanism, whereby this data can be used to inform the decision making process, ultimately increasing the precision of the operations.

Technology is playing an increasing role in agriculture and this conference will examine the role of incorporating smart technology into sustainable livestock production systems, as well as harvesting big data reservoirs to enhance resource management and underpin claims made about products. The conference will largely focus on the use of instrumentation in the management and decision-making in the life-cycle of different livestock species, with a view to efficient production systems with reduced environmental impact, increased profitability and increased welfare status of livestock. The conference has sessions focusing on PLF data and its exploitation for solutions and decision-making; PLF technology for sheep; PLF sensing and monitoring techniques for dairy animals; PLF technology for grassland management; PLF technology for milking of dairy animals; PLF product development, optimization and testing in field conditions; Monitoring animal health and behaviour; Performance and welfare of dairy animals; Controlling environment for poultry systems; Location and tracking of animal movement; and PLF technology for pigs.

The opening session of the conference will provide an overview of the role of precision technology in the pharma and dairy industries together with the future vision for precision technologies in livestock production systems. The Farmers Workshop will focus on the considered view of farmers regarding the use of technologies on their farms, factors impeding and accelerating farmer uptake of technologies and identifying what needs to be put in place to allow progress of precision farming within farming communities. The Business Models Seminar will focus on the framework required to promote the development and use of technologies, data integration associated with different livestock farming systems as well as providing examples from outside of agriculture.

Delegates will also have the opportunity to visit (i) Teagasc, Animal & Grassland Research and Innovation Centre at Moorepark, for an overview of the many aspects of on-going dairy research; (ii) the international company Dairymaster, manufacturer of hi-tech dairy equipment, including Milking Equipment, Feeding Equipment, Automatic Manure Scrapers, Milk Cooling Tanks and Health & Fertility Monitoring Systems; or (iii) a Marine Research Facility conducting increasingly significant research on climate change effects in coastal areas.

Our thanks to the Committee of the EA-PLF for accepting our bid to host the 9thECPLF; we hope that we can continue the tradition of high quality and impactful meetings which have characterised previous ECPLF Meetings.

We would like to thank all authors for their papers and presentations, the numerous reviewers for their important comments and contributions which have helped to ensure the high quality of the papers. We want to thank our organising committees and conference partners. We especially would like to thank our sponsors and supporters, without whom we could not run this conference successfully.

We hope that the 9th European Conference on Precision Livestock Farming will stimulate fruitful discussions and networking, identify common goals and develop new research collaborations. We hope that delegates enjoy their visit to Cork.

Dr. Bernadette O'Brien,
Dr. Deirdre Hennessy and
Dr. Laurence Shalloo
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The 9th European Conference on Precision Livestock Farming

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Session 1

Precision Livestock Farming Data and its Exploitation for Solutions and Decision-making (1)

Opportunities and challenges for real-time management (RTM) in extensive livestock systems

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Abstract

Extensive livestock systems face many challenges associated with their environment. They are often associated with poor quality grazing, harsh weather conditions, few or no fences and do not allow for frequent inspections of animals. In addition, the availability of appropriately skilled labour is becoming short in supply. PLF technology promises the capability to transform these systems. Four technologies are evaluated through case studies related to practical deployment and some research results. (1) LoRaWAN (Long Range Wide Area Network) often referred to as LoRa, which is an enabling, IoT, technology communicating, in this case, from animal-wearable sensors, via cloud-based computing to end-users. A network involving two LoRa gateways was established linking on-animal sensors to the 'cloud' and thence to management information. (2) GNSS - location data were collected from collars and communicated, via LoRa, to determine data transfer efficiency and location accuracy. (3) Proximity sensors - small proximity beacons on lambs and receivers with LoRA transmitters on their collared dams to assess lamb-dam pedigree information. (4) Tri-axial inertia movement units (IMU) - IMU data was communicated in real-time via LoRa enabled transmitting neck collars. The range of wearable technology provided reliable and potentially useful management information. Combined technologies provide the best technical promise but all four technologies have particular challenges in terms of costs and benefits in these extensive systems.

Keywords: real-time monitoring, extensive, LoRA, IMU, GNSS, proximity

Introduction

Real time monitoring (RTM), involving stockpeople using their eyes, ears and noses to assess the state of livestock is as old as domestication. New technology to collect data on animal behaviour and location typically involved storing data on the animal device. A shift from collecting past data to RTM now enables greater use in practical management within livestock systems.

In extensive systems, approaches to communication between devices and user through either copper wire systems or WI-FI based systems, do not work. The mobile phone network can be very effective but also has many issues of communication. The other major challenge is cost–effectiveness. In many intensive systems, individual animals have high value, or there are large concentrations of animals in the same location and opportunities for technology to improve animal output, reduce losses and save labour are frequently reported (e.g. Halachmi, 2019). These applications may involve individual wearable technology or fixed equipment in facilities with large concentrations. In extensive systems, by contrast, animals tend to be of lower value, are often widely dispersed, and typically have much lower stockperson contact. The cases for both technical effectiveness and cost/effectiveness are thus very different in extensive systems.

LoRa is fast becoming one of the key elements of the IoT revolution (Carvalho Silva *et al.*, 2017). As a low power, long range, wireless telecommunication network, it is well suited to extensively farmed environments as gateways receive data packets from LoRa

devices located within ranges typically over 20 km line-of-sight radius in rural areas and then forward the data packets to a network server (Pharm *et al.*, 2017). A single gateway can receive data from thousands of sensors. With significant promotion through cross-industry partners (e.g. LoRa Alliance) and a business model that uses license-free sub-gigahertz radio frequency bands, with network-costs embedded within the devices, it has the potential to benefit farming in the future.

GPS/GNSS is now a mature technology, but continues to develop to make it better suited for on-animal deployment in terms of spatial resolution, power requirement and cost. There are a number of businesses aiming to combine LoRa with GNSS to provide real-time monitoring for livestock. It is also feasible to obtain additional information across the LoRa network such as 'proximity' information through device-to-device communication using RFID technology, Bluetooth or NFC (near-field communication). Bluetooth technology has also been proposed to identify ewe-lamb connections (Sohi *et al.*, 2017). Already commercial equipment and services are available to utilise this approach (e.g. SmartShepherd, www.smartshepherd.com.au/).

In this paper, we will provide some case-study experiences of four different technologies under testing for extensive system applications. This will give an insight into some of the issues involved in their development and application into practice, and their potential value in extensive sheep and beef systems. We will cover LoRa as an enabling communication method, and then some work with GNSS, proximity sensors and motion sensors. Specifically, we will highlight some of the benefits and constraints of real-time communication with LoRaWAN.

Material and methods

LORAWAN communication and study site

Two LoRa gateways were deployed with some overlapping coverage. Each was connected to the internet via an ethernet connection. Data was automatically uploaded to TheThingsNetwork server (www.thethingsnetwork.org) and data provided as data downloads. Visualisations to an app was also available for some of application case studies described. Figure 1 shows an illustration of a system connecting on-animal wearable technology with the farmer. LoRa provides the communication route for the GNSS data and any other on-animal sensor data. In our case studies, this involved both proximity data and IMU data.

The topgraphy and location of the study site (Kirkton Farm, Crianlarich, Scotland) was very challenging for LoRa. The three sheep studies described were undertaken within grazing fields and larger paddocks on rolling terrain with, or surrounded by, hillocky land. 'Line of sight' to either of the two aerials was not possible from many locations within the study fields due to this topography.

Figure 1. The Communication pathway – from sensors on animals back to the stockperson

GNSS

Sheep study A involved prototype sheep collars (containing GNSS technology and communicating via LoRa) that were placed on two non pregnant ewes within a flock of 12 ewes in a small field (1.85 ha) referred to in the Results section as the target field. The field centre was 625 m from the nearest LoRa gateway. The field was not in the optimum 'line of sight' for the LoRa antennae, with some buildings and topography creating potential barriers. The two collars were configured to require a minimum of six GNSS satellites for location triangulation with data transmission frequency set to either one or five minute intervals over a 14 day period. Prior to deployment, the '1 minute' collar was placed on the top of each corner fencepost for a minimum period of 60 minutes.

Sheep study B involved other prototype collars with combined GNSS technology (locating eight satellites before a fix) and three sets of tri-axial motion sensors. In this case the centre of the field was c 250 m from the nearest LoRa gateway antennae, with much of the field, including some narrow ravines, with no direct line of sight to either of the two gateways. Data were collected from five sheep amongst a small flock for 32 days.

Proximity

Sheep study C involved data collected from a small flock of 20 Scottish Blackface ewes and their lambs (n = 40). Collars were fitted to eight of the ewes and eighteen lambs over a three-week period. Each ewe collar had a printed circuit board with a Bluetooth proximity sensor and a LoRa communication module set to communicate every hour. Each lamb had a small collar with a proximity beacon. Firmware on the ewe collar identified the five closest lamb beacons over the hour period and communicated the identity of these beacons, together with the accumulated Received Signal Strength Indication (RSSI, a measure of signal strength) for each beacon, over each deployment.

Motion Sensors

This element of research was conducted alongside the GNSS study B above. The five collars incorporated both GNSS and a set of three tri-axial motion sensors. Data were recorded at 10 Hz for each of the axis, the magnitude of the vectors were computed after preliminary groundtruthing of specific behaviours of interest (grazing, lying, walking), were then mapped to the magnitude outputs. The condensed data were then sent through LoRa as a set of 11 indices every two minutes. Whilst some 'ground-truthing' behavioural observations were conducted, this element of the study is not described in this paper, here we focus on the simple feasibility of communicating a number of condensed elements of the very large sets of initial IMU data.

Results and discussion

The most fundamental technical need for the LoRa element is to be able to communicate data, without or with, manageable error. Figure 2 shows data communication intervals for two sheep collars, set with a two minute interval. As noted above, these sheep were in the same grazing area, but within a very hillocky paddock with less than perfect line-of-sight between sheep locations and either LoRa gateway antennae. The pattern of communications shows that 95% of upload of data packets from collar to network server were within two minutes +/- 10sec, with subsequent pick up of data at each two minute interval with the residual number of lack of data packet transfers halving at each two minute period. The near perfect alignment between the two collars (the other three collars had near identical patterns) illustrates that very little of the communication drop off is likely to be due to within-field issues caused by differences in sheep location, but more likely performance issues with the GNSS not registering the minimum number of satellites. Longer gaps in transmissions were likely to be due to breaks in communication

between the gateway and network server affecting all collar data sets equally. One clear issue with real-time data transmission illustrated here is that data collected and collated on the collar during each programmed duty cycle is lost if it is not received by a gateway or if the gateway to network server connection is down. The collar/LoRa just moves on and sends the next duty cycle of data.

The spread of mapped points from the collars in Study A at static points were in excess of 20 m (10 m radius from the centre), as a result of standard GNSS error. Many sheep location 'hotspots' linked to both grazing and camping areas for the two collared sheep were in close proximity to the fence line with a high proportion of locations on the outside of the fenceline and simplistically these would be allocated to another field rather than the target field. As shown in Table 1, for Sheep 1, with 15,976 locations at one minute location cycles over 14 days, it was found that 29% of locations were outside the best assessment of the fence line boundary. Stepwise combinations of rolling average and a 10 m buffer zone reduced the number of locations not allocated to the target field to just nine locations or 0.05% (1 in 1,775) and critically the numbers of time-consecutive locations outside the buffered target field was zero. For Sheep 2 with a GNSS cycle of five minutes, with 1,543 locations over 11 days, 21.3% of raw data points were outside the fenceline. With a combination of rolling average and 10 m external buffer zone effectively placed every location within the field.

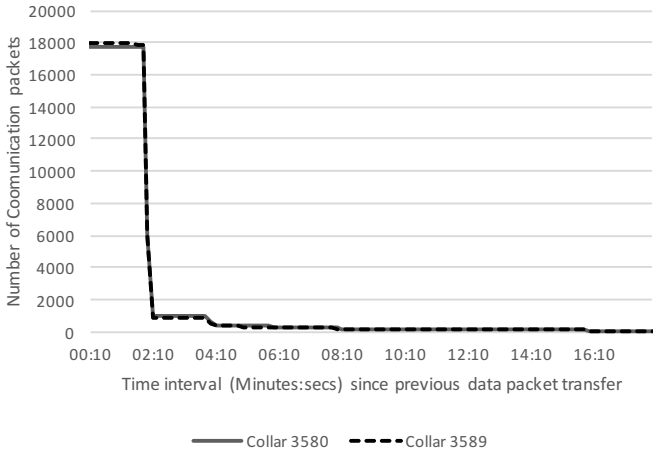

Figure 2. Performance of LoRA data packet transfers for two collars with a two minute duty cycle over 26 days

Table 1. GNSS – animal location – which field is the sheep in?

	Outside fenceline (of raw data points)	Outside when using a 10 point rolling average	Outside fenceline use 10 m buffer	Outside fenceline methods combined
Sheep 1 (1 min. intervals)	29% (15,333)	20%	1.5%	0.05%
Sheep 2 (5 min. intervals)	21.3 (1,543)	1.9%	1.3%	0.001%

In Sheep Study C, all ewe collars displayed uneven distributions towards certain lambs during each deployment phase. Chi-square analyses estimated for each ewe collar identified highly significant results in favour of the related lambs ($p < 0.0005$). There were clear differences between the mean number of contacts made by each ewe and her related lambs (29.51 ± 1.7), and the unrelated lambs (2.04 ± 0.14) ($p < 0.0005$) as illustrated in Figure 3 for one ewe collar with all collared lambs. All ewe/lamb pairings had very similar patterns. In addition, there were also large differences in RSSI for the contacts that were registered. The means of related (-80.61 ± 0.92) and unrelated (-91.12 ± 0.31), as illustrated in distribution form in Figure 4, were again highly significantly different ($p < 0.0005$). So, not only did related lambs register dramatically more contacts, the nature of these contacts were stronger.

Overall, the highly significant results obtained, in terms of both contact number and distance associated with the contacts, suggests this is a very useful method to establish reliable ewe and lamb relationships. This could help to enable extensive hill flocks to benefit from genetic improvement, although sire identification would also need to be carried out. Nonetheless, the ability to relate the performance of the ewe to her lambs would provide valuable information in terms of traits such as lamb survival and growth.

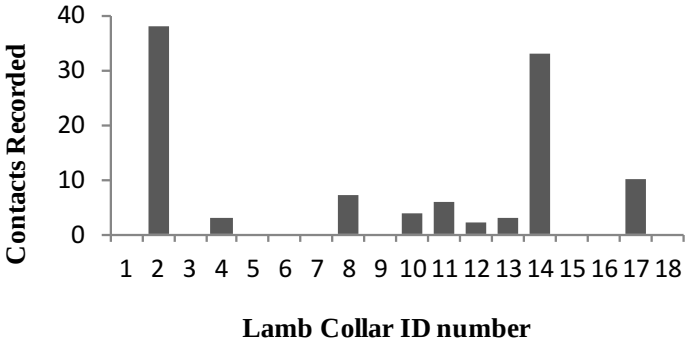

Figure 3. Ewe Collar contacts with different lambs (Lambs 2 and 14 are related twin lambs)

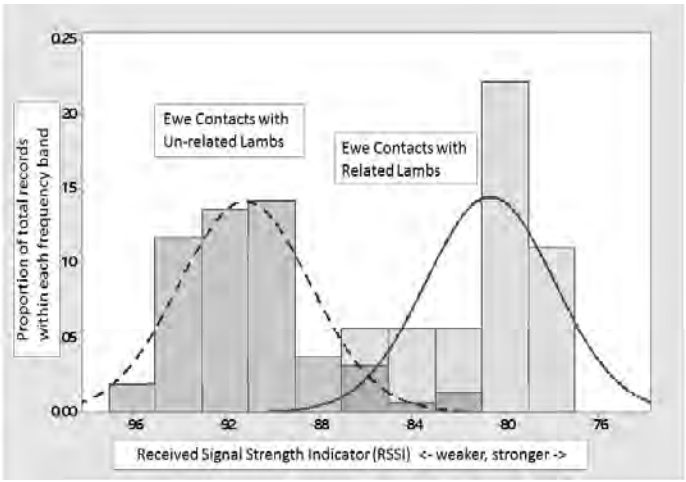

Figure 4. Data from ewe/lamb proximity pairings communicated showing Signal Strength (RSSI) distributions between proximity-logged related and un-related ewes/lambs

Cost Benefit Analysis

There are two main issues linked to the adoption of real-time monitoring technology; firstly, will the technology provide useful information for decision support and secondly, will there be satisfactory cost/benefit for the technology uptake.

There are then two further elements of improved production. The first is linked to direct gain in the number of live animals available for sale through improved survival of both adult breeding animals and young growing animals. The high losses of lambs in extensive systems are well documented (e.g. Waterhouse, 1996). There are many life/death scenarios in extensive systems, and there are many situations where interventions by stockpeople could make a difference. The challenge is to ensure that the location of any problem can be highlighted to the stockperson but that there is then sufficient time and resources to have a chance of success. With wearable technology combining real-time location and diagnosable behaviour, then both the location and putative diagnosis of the issue could be communicated to the stockperson.

A second element of productive gain in these systems is the potential to increase the size and value of the livestock sold. Increases in liveweight of weaned lambs or calves would typically provide an economic gain. The biological mechanism by which this could be achieved via PLF technology is challenging to ascribe. Using a well-documented PLF approach for sheep, using so-called Targeted Selective Treatment (TST) for stomach worm control, there were clear benefits in terms of more sustainable use of anthelmintic drugs, and some limited input savings, but the main conclusion of a series of studies is that body weight change was not affected (e.g. Morgan-Davies *et al.*, 2018).

The proximity system for lamb maternal pedigree has a simpler set of cost benefits. Commercial services using tissue samples and DNA analysis cost upwards of £10 per lamb for lamb-ewe-ram diagnosis. Using proximity sensors, an accurate pedigree of lamb-ewe appears feasible within one week, allowing multiple uses of the same equipment. The commercial service being offered in Australia provides further evidence that commercial cost/benefit exists.

Steenvold *et al.* (2015), showed no benefits in productivity, savings or changes in technical management after implementation of sensor systems on a large number of dairy farms, so it is important that the PLF science community asks questions about cost/benefit alongside studies of technical proficiency. Furthermore, differences between intensive and extensive systems should also considered.

Conclusions

LoRa communication within the range of a LoRa gateway network was shown to be very effective, though may lead to data losses through loss of connection across the different stages of data transfer. There are also constraints of data through data packet length and data transmission interval (which affects power use). Advantages are that data are real-time, so data transmissions can be seen and therefore, it is possible to problem-solve issues of both communication and data acquisition. Limits of data packet length forces decisions on which data can be collected and communicated, rather than 'everything'. On-going developments with LoRa networks, and with gateway locations in remote environments, are needed. There are challenges for remote, extensively farmed areas with poor coverage of mobile phone networks and connections to the internet. Knowing where animals are in real time is valuable, especially in extensive environments. This complements other 'behaviour' information or alerts, because if an alert is received or a problem is identified then it is only through knowing where the animal is that action can be taken. For field-based systems, field location is important, but may be beyond the resolution of GNSS

without use of runs of data. Proximity sensors show the capability to provide data on dam-offspring relationships essential for animal breeding and a practical alternative to DNA testing which could be particularly valuable for sheep breeding in extensive systems. The need and financial value of real-time monitoring of this data is less clear. Combined technologies provide the best technical promise but all four technologies have particular challenges in terms of costs and benefits in extensive systems.

Cost-effective precision livestock farming technology and applications could be transformational in extensive systems, but better case studies are needed to highlight the production and welfare impacts and these should include cost/benefit analyses.

Acknowledgements

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References

Carvalho Silva, J.de, Rodrigues, J.J.P.C., Alberti, A.M., Solic, P. and Aquino, A.L.L. (2017). LoRaWAN — A low power WAN protocol for Internet of Things: A review and opportunities. 2nd *International Multidisciplinary Conference on Computer and Energy Science (SpliTech)*, Split, 1–6.

Halachmi, I., Guarino, M., Bewley, J. and Pastell, M. (2019). Smart animal agriculture: Application of Real-Time sensors to improve animal Well-Being and production. *Annual Review of Animal Biosciences,* 7(1): 403–425.

Morgan-Davies, C., Lambe, N., Wishart, H., Waterhouse, T., Kenyon, F., McBean, D. and McCracken, D. (2018). Impacts of using a precision livestock system targeted approach in mountain sheep flocks. *Livestock Science,* 208: 67–76.

Pattinson, S.E., Waterhouse, A., Ashworth, S.A. and Wyllie, J.T.B. (1994). Cost/benefit analysis of nutritional and shepherding inputs at lambing in an extensive hill sheep system. 45th *Meeting of European Assocation of Animal Production,* Edinburgh.

Pham, C., Ferrero, F., Diop, M., Lizzi, L., Dieng, O. and Thiaré, O. (2017). Low-cost antenna technology for LPWAN IoT in rural applications. 7th *IEEE International Workshop on Advances in Sensors and Interfaces (IWASI)*, Vieste, 121–126.

Sohi, R., Trompf, J., Marriott, H., Bervan, A., Godoy, B.I., Weerasinghe, M., Desai, A. and Jois, M. (2017). Determination of maternal pedigree and ewe–lamb spatial relationships by application of bluetooth technology in extensive farming systems. *Journal of Animal Science,* 95(11): 5145–5150.

Steeneveld, W., Hogeveen, H. and Oude Lansink, A.G.J.M. (2015). Economic consequences of investing in sensor systems on dairy farms. *Computers and Electronics in Agriculture*, 119, 33–39.

Waterhouse, A. (1996). Animal welfare and sustainability of production under extensive conditions—A european perspective. *Applied Animal Behaviour Science,* 49(1): 29–40.

The effect of timing of a single-dose artificial insemination on sow fertility

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Abstract

Daily visual estrus detection is commonly considered the best indicator of a good timing for inseminating sows. Since each sow has a different estrus duration and semen viability is generally considered to last 24 hours, most breeders end up inseminating their sows multiple times during estrus. This approach has proven to yield good fertility results, but one can be skeptical about its optimality. We developed a different approach using algorithms that consider both sow behaviour and worker estrus observations to predict the optimal timing for insemination. Our approach allows breeders to reduce the average number of inseminations from an industry average of 2.3–1.35, while keeping good reproduction performance. Over the last two years, data has been collected from nine commercial farms that use our approach. This is a unique source of information about sows with only one insemination per estrus cycle. In fact, the exact date and time of the insemination, the onset and end of the estrus symptoms as seen by farm workers, and fertility results were recorded for more than 12,000 estrus cycles with a single insemination. An in-depth analysis of this data suggests that the result of a precise single-dose insemination is highly dependent on the timing of the insemination, as well as that only a half-day difference can have a significant impact on conception rate (up to 12%). This study pinpoints the right timing to inseminate sows within the estrus period for different estrus durations and sets the base for further improvement of precision breeding methods.

Keywords: sow fertility, single-dose insemination, precision breeding, artificial intelligence, artificial insemination

Introduction

Finding the right time to inseminate sows is a daily challenge for pig breeders and has an important impact on farm efficiency. In absence of a way to precisely identify an optimal timing for insemination relative to ovulation, daily visual estrus detection is commonly considered as the best indicator of a good timing for insemination. To ensure that the insemination is carried in time with ovulation, breeders generally inseminate sows once a day during estrus (Knox, 2016). This approach is subjective, and its quality is highly dependent on worker observations.

Research has shown that, considering sperm capacitation and lifetime of gametes, the optimal moment to inseminate is 24 hours to 0 hour before ovulation (Soede *et al.*, 1994). Outside of this interval, the fertility and the litter size have been shown to decrease. In fact, Kemp & Soede (1996) observed that an insemination carried before this 24-hour interval results in 39.6% unfertilised eggs, while a later insemination results in 25% unfertilised eggs.

The timing of ovulation is highly variable and dependent on the duration of estrus. The timing of ovulation is generally positively correlated with the duration of estrus (Almeida *et al.*, 2000; Weitze *et al.*, 1994). However, the onset of estrus was qualified as a bad predictor of the moment of ovulation (Steverink *et al.*, 1999). Some authors suggested to use the weaning-to-estrus interval (WEI) to predict the optimal moment to inseminate in view of the fact that the duration of estrus is negatively correlated with the WEI (Steverink *et al.*, 1999; Weitze *et al.*, 1994). Consequently, the moment of ovulation is negatively correlated

with the WEI (Kemp & Soede, 1996; Knox & Zas, 2001; Weitze *et al.*, 1994). Ovulation is generally known to occur between 60% and 86% through estrus, independently of its duration (Almeida *et al.*, 2000; Anuvongnukroh *et al.*, 2004; Bracken *et al.*, 2003; Martinat-Botté *et al.*, 1997; Mburu *et al.*, 1995; Nissen *et al.*, 1997; Soede *et al.*, 1992; Soede *et al.*, 1995; Soede *et al.*, 1997; Urasopon *et al.*, 2003; Weitze *et al.*, 1994).

Most studies used only a small number of sows (on average 115 sows per study) in an experimental context. This paper aims to evaluate how the timing of a single-dose insemination affects fertility in large-scale commercial sow farms and how this compares with literature.

Material and methods

Animals and housing

12,280 estrus cycles (from weaning to Day 9 post weaning) were analysed from nine commercial farms equipped with the PigWatch system in Canada, USA, Chile, Spain and Belgium (Table 1). PigWatch is a computerised system using a motion sensor installed on top of each sow stall. It uses artificial intelligence algorithms to predict the best timing for insemination based on real-time sow behaviour monitored during the first days post weaning. PigWatch allows the reduction of the average number of inseminations from an industry average of 2.3 to around 1.35. The data were collected from October 2016 to December 2018. The initial database of 38,513 estrus cycles was sorted to exclude data that seemed unreliable. In fact, not all participating farms always correctly input date and time of inseminations, end of estrus or conception rate results. When a significant number of sows in a group showed abnormalities, the whole group was automatically excluded from the analysis. Such abnormalities include, but are not limited to, pregnant sows that have no insemination data, sows with no date for the end of estrus, and batches with an average conception rate above 97%. The sows were housed in individual stalls after weaning. The genetics of the animals and the diet differed among farms.

Table 1. Number of analysed estrus cycles per farm and average parity

Farms	Estrus cycles (n)	Average Parity	Analysis start date
Farm 1	74	NA	October 2018
Farm 2	2,473	4.81 ± 1.84	October 2016
Farm 3	780	4.55 ± 1.88	May 2018
Farm 4	2,071	5.42 ± 2.44	October 2017
Farm 5	809	3.93 ± 2.26	May 2017
Farm 6	627	4.54 ± 2.48	February 2018
Farm 7	5,594	4.33 ± 1.76	December 2017
Farm 8	235	3.64 ± 1.27	June 2018
Farm 9	105	4.20 ± 1.93	June 2018

Estrus detection and insemination

For all estrus cycles, the timing of the onset and end of estrus (standing heat) as identified by farm workers were recorded in the PigWatch software. The actual moment of insemination was also recorded systematically. Post-cervical artificial insemination (PCAI) was used in all farms and the timing of insemination was determined by the PigWatch system.

Estrus detection was carried out every 24 hours from weaning to 7–10 days post weaning. All participating farms used a boar and a Contact-O-Max boar cart (Ro-Main, Saint-Lambert-de-Lauzon, Québec, Canada) to maximise snout-to-snout contact and thus maximize the sow's physiological response, as per the PigWatch protocol. For the analysis, the onset of estrus was determined as the moment at which the standing reflex was first observed minus 12 hours, and the end of estrus as the time the sow stopped showing the standing reflex minus 12 hours. The moment of the observation of the standing reflex is considered to be at 6:00 am for all estrus cycles, independently of the actual estrus detection time that was between 5:00 am and 9:00 am. Pregnancy was checked approximately 35 days after the insemination with an ultrasound system for all sows that did not return to estrus before.

Data analysis

The timing of insemination for the different sows were grouped in four x 12-hour classes (AM-1 is 12:00 am to 11:59 am of the first day in heat; PM-1 is 12:00 pm to 11:59 pm of the first day in heat; am-2 is 12:00 am to 11:59 am of the second day in heat; pm-2 is 12:00 pm to 11:59 pm of the second day in heat) but sows were never inseminated before 5:00 am or after 6:00 pm. Only sows with an estrus duration of three days or shorter were kept in the analysis as there were too few longer estrus cycles. The analysis was done independently for each estrus duration, since the one-day estrus cycles have only two classes while two-day and three-day have four classes. A logistic regression was made with a Tukey test to highlight the statistical differences between the classes (time intervals). The classes and farms were taken as factors of the model and alpha = 0.05. To compare with literature, the timing of ovulation was considered to occur 66% throughout the estrus duration. The conception rates presented in this study are adjusted means.

Results and discussion

One-day estrus

The conception rate is higher when the sow is inseminated in the afternoon of the first day of estrus ($P = 0.024$). The conception rate for the am-1 interval is 76.23% and is 82.41% for the pm-1 interval (Figure 1). In theory, the ovulation occurs at approximately 10:00 am for these sows, therefore, the obtained conception rate is not directly in line with literature. We were expecting a better conception rate in the morning as it was more likely to be in the interval of 0 hour to 24 hours before ovulation (Soede *et al.*, 1994). This difference could be explained by the precision of the onset of estrus due to the low frequency of heat detection. In fact, the precision of the interval between the onset of estrus and the time of ovulation decreases when estrus detection is carried once a day (Almeida *et al.,* 2000).

Two-day estrus

The conception rate of sows with a two-day estrus duration is 90.31%, 89.05%, 77.37%, and 71.19% for the intervals AM-1, PM-1, AM-2 and PM-2, respectively. The conception rate seems to decrease when sows are inseminated on the second day of estrus. However, there is an interaction between the intervals and the farms ($P < 0.01$) and thus global results cannot be interpreted (Figure 2).

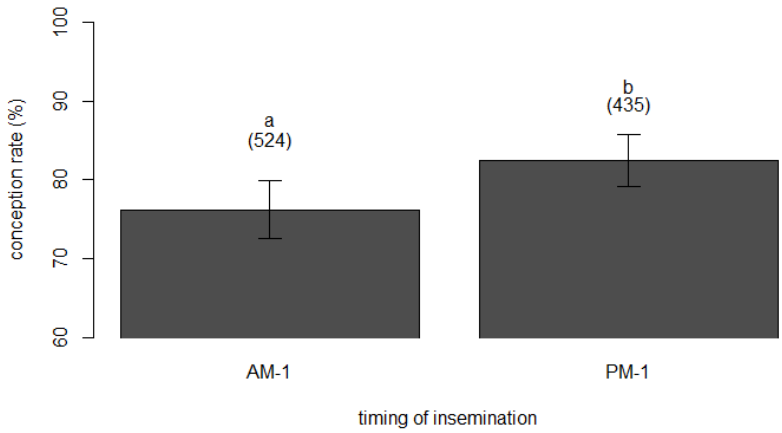

Figure 1. Conception rate of sows with one-day estrus duration and a single-dose insemination according to the timing of insemination. Different superscript letters indicate that variables were significantly different ($P < 0.05$). The numbers in brackets represent the number of estrus cycles analysed per interval

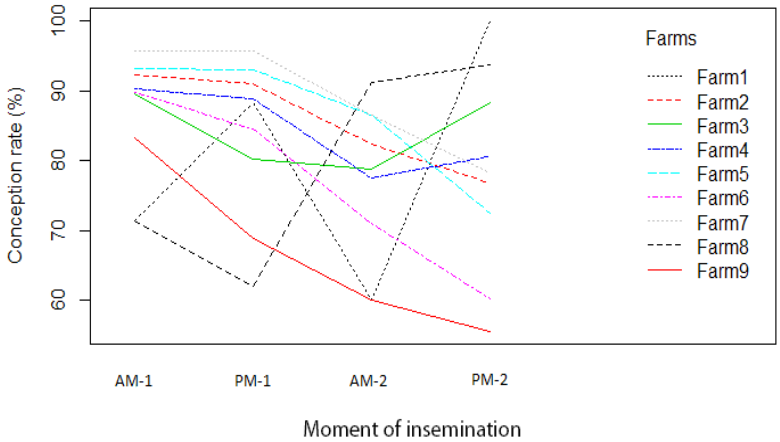

Figure 2. Conception rate of sows with two-day estrus duration and a single-dose insemination according to the moment of insemination for each farm of the study

The farms with a small number of estrus cycles seems to be those with erratic behaviour (Farm 1: n=74; Farm 3: n=780; Farm 8: n=235). It is important to note that Farm 1 and 8 have been using the PigWatch system for a very short period and are still learning how to use the system properly. Farm 3 is one of the first farms equipped with the PigWatch system, but the number of cycles kept for analysis is very low. This means that most cycles were excluded due to abnormal data. We can therefore have some doubts regarding the precision of the input data from this farm. Farm 1, 3, and 8 were therefore eliminated from the data to see the general trend. Without these three farms, the interaction between farms and intervals is not significant ($P = 0.073$). The adjusted mean is 91.11%, 90.08%, 77.46%, and 70.32% for the intervals AM-1, PM-1, AM-2 and PM-2, respectively (Figure 3). In theory, ovulation occurs around 2:00 am on the second day of estrus. Consequently,

the best moment to inseminate according to literature is on the first day of estrus. The results of our study show the same trend, which is that fertility is optimal when sows are inseminated on the first day of estrus. A half-day difference has a significant impact on conception rate (12.62%).

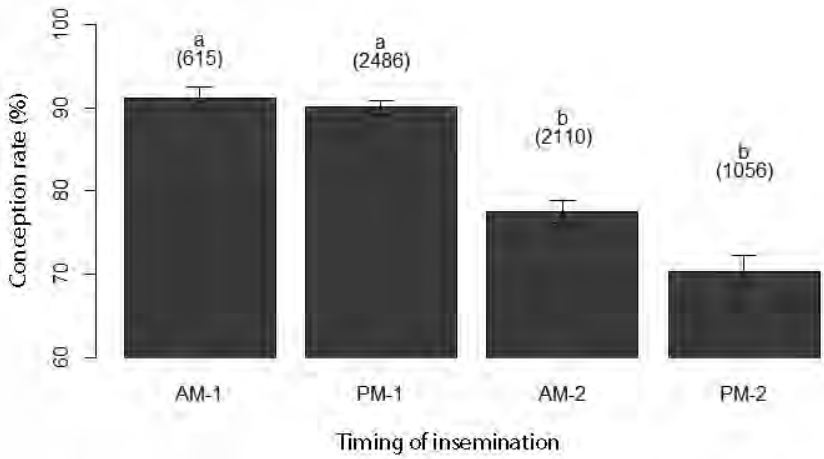

Figure 3. Conception rate of sows with a two-day estrus duration and a single-dose insemination according to the timing of insemination for Farm 2, 4, 5, 6, 7, 9. Different superscript letters indicate that variables were significantly different ($P < 0.01$). The numbers in brackets represent the number of estrus cycles analysed per interval

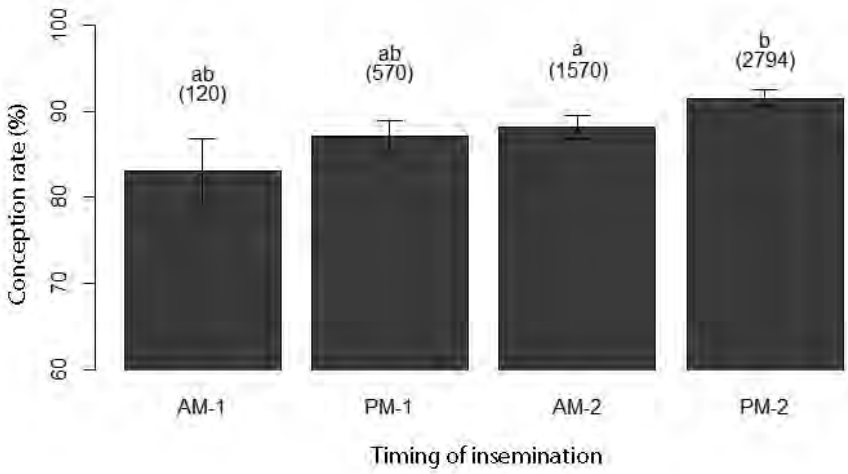

Figure 4. Conception rate of sows with a three-day estrus duration and a single-dose insemination according to the timing of insemination. Different superscript letters indicate that variables were significantly different ($P < 0.05$). The numbers in brackets represent the number of estrus cycles analysed per interval

Three-day estrus

The conception rate of each interval is 83.02%, 87.05%, 88.13%, and 91.52% for AM-1, PM-1, AM-2 and PM-2, respectively (Figure 4). The only observed statistical difference is between PM-2 and AM-2 ($P = 0.0425$). In theory, ovulation occurs around 6:00 pm on the second

day of estrus. We should therefore observe better fertility on the second day of estrus in comparison with the first. Even though the conception rate on the first day of estrus seems not as good as the conception rate on the second day, this trend is not statistically significant and cannot be confirmed. Based on our results, it seems important not to inseminate too early (before AM-2) to maximise conception rate for sows with a three-day estrus duration.

The absence of cycles with a unique insemination on the third day of estrus makes it impossible to observe the effect of inseminating past the second day of estrus. It is important to note that the PigWatch system can create a bias in the study by predicting the length of the estrus cycle and targeting a supposedly optimal timing of insemination, resulting in fewer very early or very late inseminations. Thus, the timing at which each sow was inseminated was not determined randomly but carefully chosen by a predictive algorithm aiming to optimise reproduction performance.

Conclusion

The timing of a single-dose insemination is important to obtain optimal results. Our data suggests that the result of a precise single-dose insemination is highly dependent on the timing of the insemination, as well as that only a half-day difference can have a significant impact on conception rate (up to 12%). Furthermore, our results are in line with the conclusions presented in literature, i.e. that the optimal moment to inseminate is between 24 hours and 0 hour before ovulation, and that ovulation occurs within 60–77% throughout the estrus period.

Since this research was carried under commercial farm conditions, our results give an indirect evaluation of the best moment to carry a single-dose insemination in such conditions. Our evaluation is based on conception rate rather than direct observation of the ovulation as in other research projects. From our analysis, it seems that a suitable way to predict an optimal timing for a single-dose insemination is to predict the estrus duration, which the PigWatch system does from behaviour data. This study pinpoints the right timing to inseminate sows within the estrus period for different estrus durations and sets the base for further improvement of precision breeding methods.

Precision breeding achieved through precise single-dose insemination promises to reduce dependency on skilled labour, optimise reproduction performance, maximise the use of the best boars, and ultimately accelerate genetic improvement.

Acknowledgements

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References

Almeida, F.R.C.L., S. Novak, and Foxcroft, G.R. (2000). The Time of Ovulation in Relation to Estrus Duration in Gilts. *Theriogenology,* 53(7): 1389–96.

Anuvongnukroh, Woravit, Chaowaphan Yinharnmingmongkol, Sutthatip Punieam, Padet Tummaruk, and Annop Kunavongkrit (2004). The effect of parity number, body condition score, backfat thickness and weaning to oestrus interval on the time of ovulation. *The Thai Journal of Veterinary Medicine,* 34(2): 69–75.

Bracken, C.J., Safranski, T.J, Cantley, T.C, Lucy, M.C, and Lamberson, W.R. (2003). Effect of Time of Ovulation and Sperm Concentration on Fertilization Rate in Gilts. *Theriogenology,* 60(4): 669–76.

Kemp, B, and N M Soede (1996). Relationship of Weaning-to-Estrus Interval to Timing of Ovulation and Fertilization in Sows. *Journal of Animal Science,* 74(5): 944.

Knox, R.V. (2016). Artificial Insemination in Pigs Today. *Theriogenology*, Swine Reproduction, 85(1): 83–93.

Knox, R V, and S L Zas (2001). Factors Influencing Estrus and Ovulation in Weaned Sows as Determined by Transrectal Ultrasound. *Journal of Animal Science,* 79(12): 2957.

Martinat-Botté, F., Forgerit, Y., Maurel, M.C., Corbé, H., Bernelas, D., Mercat, M.J., Guillouet, P. and Terqui, M. (1997). Étude des moments d'ovulation et d'insémination chez la truie et de leurs conséquences sur la taille de la portée en élevages. *Journées de la Recherche Porcine en France*, 29: 103–108.

Mburu, J.N., Einarsson, S., Dalin, A.-M., and Rodriguez-Martinez, H. (1995). Ovulation as Determined by Transrectal Ultrasonography in Multiparous Sows: Relationships with Oestrous Symptoms and Hormonal Profiles. *Journal of Veterinary Medicine Series A,* 42 (1–10): 285–92.

Nissen, A.K., N.M. Soede, P. Hyttel, M. Schmidt, and L. D'Hoore (1997). The Influence of Time of Insemination Relative to Time of Ovulation on Farrowing Frequency and Litter Size in Sows, as Investigated by Ultrasonography. *Theriogenology,* 47(8): 1571–82.

Soede, N.M., Noordhuizen, J.P. and B. Kemp (1992). The duration of ovulation in pigs, studied by transrectal ultrasonography, is not related to early embryonic diversity. *Theriogenology*, 38: 653–666.

Soede, N.M., F.A. Helmond, and B. Kemp (1994). Periovulatory Profiles of Oestradiol, LH and Progesterone in Relation to Oestrus and Embryo Mortality in Multiparous Sows Using Transrectal Ultrasonography to Detect Ovulation. *Reproduction,* 101(3): 633–41.

Soede, N.M., C.C.H. Wetzels, W. Zondag, M.A.I. de Koning, and B. Kemp (1995). Effects of Time of Insemination Relative to Ovulation, as Determined by Ultrasonography, on Fertilization Rate and Accessory Sperm Count in Sows. *Reproduction,* 104(1): 99–106.

Soede, N.M. et B. Kemp (1997). Expression of oestrus and timing of ovulation in pigs. *Journal of Reproduction and Fertility*, Supplement, 52: 91–103.

Steverink, D.W.B., N.M. Soede, G.J.R. Groenland, F.W. van Schie, J.P.T.M. Noordhuizen, and B. Kemp (1999). Duration of Estrus in Relation to Reproduction Results in Pigs on Commercial Farms. *Journal of Animal Science,* 77(4): 801–9.

Urasopon, N., Tantasuparuk, W. and Techakumphu, M. (2003). The effects of weaning-to-oestrus interval on the expression of oestrus and the timing of ovulation in sows. *The Thai Journal of Veterinary Medicine*, 33: 55–62.

Weitze, K.F., H. Wagner-Rietschel, D. Waberski, L. Richter, and J. Krieter (1994). The Onset of Heat after Weaning, Heat Duration, and Ovulation as Major Factors in AI Timing in Sows. *Reproduction in Domestic Animals,* 29(5): 433–43.

Monitoring body temperature in chickens during an infectiology experiment using a sensor-based telemetric system

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Abstract

Among physiological measures, body temperature variation is an important indicator of the health and well-being of animals. This parameter is usually recorded using rectal or cloacal probes, which can result in stress-induced hyperthermia and bias data. The aim of this study was to evaluate the interest of a telemetric sensor (Anipill ®) in the continuous monitoring of body temperature in chickens. This system is composed of a miniaturized electronic sensor (capsule) which uses wireless technology to transmit data up to three meters to a dedicated monitor. A single monitor can track up to 16 capsules. The system was first tested in healthy chickens to evaluate its safety. Oral administration was easily performed for chickens (weight 727 ± 65 g). The sensor persisted in the gizzard without adverse effect or macroscopic lesion during the observation period of 14 days. Temperatures measured with the sensors were correlated with the cloacal temperature ($r = 0.34$, $p = 0.0001645$). In addition, the system revealed temperature variations likely due to the circadian rhythm in the chickens. In a second experiment, temperature variations were recorded after inoculating animals with a very virulent strain of infectious bursal disease virus (IBDV). The inoculated animals were clinically monitored in parallel using a validated scoring regarding IBDV. Temperature monitoring revealed a dramatic hyperthermia following infection. Temperature variations were a more sensitive indicator of disease than the monitoring through clinical scoring. This sensor could be used for example to prevent heatstroke in poultry buildings or to improve models in infectiology research for poultry.

Keywords: chicken, temperature telemetry, safety, infectious bursal disease, clinical monitoring

Introduction

Among physiological measures, body temperature variation is an important indicator of the health and well-being of animals. This parameter is usually recorded using rectal or cloacal probes because this procedure of measurement is considered as cheap and easy to execute both in live and anesthetised animals (Scudder *et al.*, 2009). However, temperature measurement procedure using rectal or cloacal probes can result in stress-induced hyperthermia and bias data. For instance, Clark *et al.*, 2003 reported that this procedure results in long-lasting elevations in body core temperature in rodents. Its influence may be especially crucial in pharmacological studies because the effects of many drugs depend upon basal temperature and the activity state of animals (Kiyatkin & Brown, 2005). In addition, Bae *et al.* (2007) reported a strong impact of repeated body temperature measurements in rodents, with a 0.6 °C to 0.7 °C rise in body temperature after each procedure. Thus, it can be assumed that rectal temperature measurement has an impact on animal welfare when repeated measures are made. Under these considerations, the use of telemetric devices allowing continuous temperature measurement could be a possible solution. Regarding poultry experiments, this possible alternative must fulfill some specifications: i) It should not be too large for easy oral administration or minimally invasive surgical implantation in smaller animals; ii) It should be able to operate with several surrounding sensors and

a single monitor should be sufficient for several animals; iii) The distance transmission should be high enough for easy data collection and its autonomy should cover several days. Considering these specifications, we evaluated the interest of a telemetric sensor (Anipill ®) in the continuous monitoring of body temperature in chickens. This sensor was previously tested in the rat by intraperitoneal route (Chapon *et al.*, 2012). In a first step, the system was tested in healthy chickens to evaluate its safety. In a second step, it was tested on animals infected with a very virulent strain of infectious bursal disease virus.

Material and methods

Presentation of the tested device (Anipill®)

The tested device is composed of an electronic capsule integrated in a flex coating of biocompatible resin (Figure 1) with the following characteristics: size (length = 17.7 mm; diameter = 8.9 mm), weight (1.7 g) and accuracy of 0.1 °C. The user can pre-select data sampling frequency of the capsule from 30 s to 15 min (30 s, 2 min, 5 min or 15 min). The capsule uses wireless technology to transmit data up to three meters to a dedicated monitor for recording and direct reading. A single monitor can track up to 16 capsules simultaneously.

Figure 1. ANIPILL® Caps

Experiment steps

Two successive experiments were set up. The studies were conducted in an approved establishment for animal experimentation (n°C-22- 745-1) in accordance with national regulations on animal welfare and after approval of the protocols by the host laboratory ethical committee (registered at the national level under n°C2EA-16).

Safety experiment

We tested safety of the system in 20 specific pathogen-free (SPF) White Leghorn healthy chickens (mean weight ± standard deviation: 727 ± 65 g). At day 0 (D0), animals were identified using a wing tag, weighed, then transferred into two pens. In each pen, five animals were orally administered a capsule set up to measure temperature every 15 minutes (group A); five chickens remained as control animals without capsule (group C). After an acclimatation period of three days, and from D3 to D14, cloacal temperature was measured on all animals (group A and C) using a medical thermometer on a daily basis. Animals were weighed on D0 and then on D3, D7, D10 and D14 in order to calculate their daily weight gain. Data sampling frequency was selected with 15 minutes interval. On D14, all animals were humanely euthanized and necropsy was performed with careful examination of the gizzard.

Challenge experiment

Four days before inoculation, five-week-old SPF White Leghorn chickens were randomly assigned to two groups (infected and mock-infected) of 11 individuals each and individually identified with coloured leg rings. Five and 11 individuals were orally administered a capsule in the mock-infected and infected group, respectively (sampling frequency: 15 minutes). Chickens were then transferred into biosafety level two isolators. After an acclimatation period of four days, chickens from the infected group were inoculated intranasally (200 µL per bird) with 10^6 median B cell infective dose ($TCID_{50}$) (Soubies *et al.*, 2018) of the very virulent strain 89,163 of infectious bursal disease virus (IBDV) (Eterradossi *et al.*, 1992); mock-infected chickens received 200 µL of diluent. Animals were then checked daily for 10 days following inoculation and clinical signs were recorded using a symptomatic index ranging from zero (no clinical sign) to three (severe clinical signs that meet the ethical endpoint or dead birds) as previously described (Le Nouen *et al.*, 2011). Ten days post-inoculation, chickens were humanely euthanized and necropsy was performed.

Data analysis

The first safety criterion concerned the non-difference in rectal temperature between animals with and without Anipill capsule. This difference was tested throughout the experiment (D0, D3, D7, D14) by a mixed analysis of variance. Time and whether or not the animals received a capsule were considered fixed effects; animals are considered as a random effect. A time first-order autoregressive correlation structure was considered and the 'lme' function from the 'lme' R package was used. The Type I error of the factor 'capsule' was interpreted. In addition, in order to conclude about the equivalence in temperature between the groups that received or did not receive a capsule, the Type II error was also calculated with the 'power.anova.test' function from the 'stats' R package.

The second safety criterion was related to the non-difference in weight between animals with and without capsule. This difference was tested in the same way (i.e. mixed analysis of variance) as above.

The last criterion was about the relationship between rectal temperature and temperature obtained from the capsules. This link was studied with the Pearson correlation between those two measures. The 'cor.test' function from the 'stats' R package was used.

Results

Safety experiment

Oral administration of the capsule was easily performed for all animals. After introduction into the esophagus, soft massaging of the throat ensured movement of the capsule down the crop. At the end of the experimental period, that is 14 days after implantation, during necropsy, all capsules were found in the gizzard, and no macroscopic gizzard lesion was found in implanted nor control animals, as shown in Figure 2.

Figure 3 displays temperature data from one chicken over the entire study period, with cloacal temperature and temperature data recovered from the capsule. Data from the capsule revealed decreases in temperature when no intervention took place in the facility and during nighttime, except from D6 to D7 in the night where a disruption of the ventilation system occurred. It also revealed temperature increase during interventions, for example, when cleaning the facility or weighing the animals.

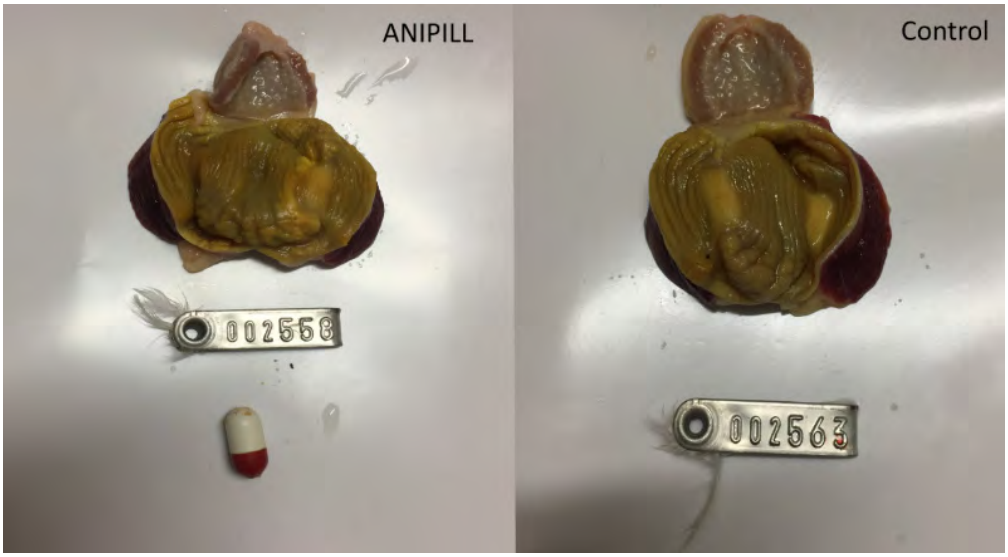

Figure 2. Gizzards of one animal in group A (Anipill) and one animal in group C (Control), on D14, showing no macroscopic lesion

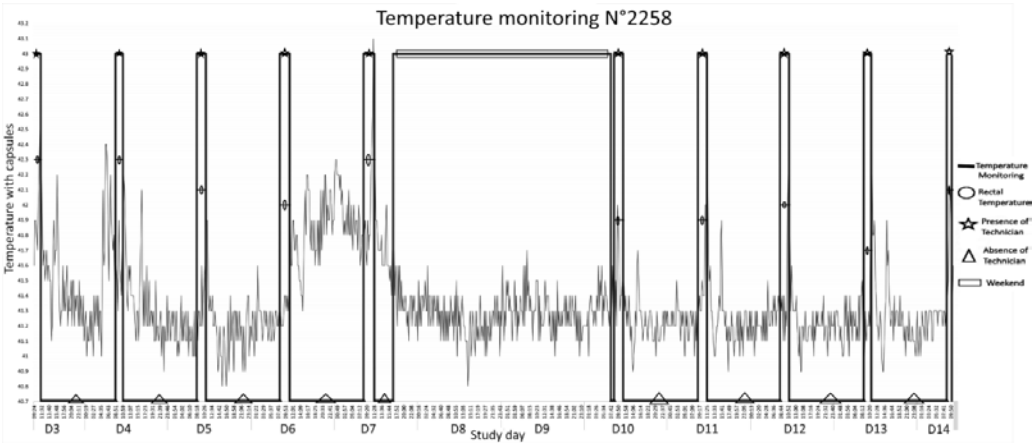

Figure 3. Temperature data from one chicken over the entire study period, with cloacal temperature and temperature ○ recovered from the capsule (gray spiky curve). Data also show temperature variation with (presence of technician ☆) or without (absence of technician △) intervention in the facility and during the weekend period ▭

Figure 4 displays the mean cloacal temperature data in groups A and C as well as the mean temperature data in group A 15 minutes before taking the corresponding cloacal temperature. No statistically significant difference was observed between the cloacal temperatures of the two study groups ($p = 0.82$). On the other hand, cloacal temperatures values and those recorded by the capsules were significantly correlated ($r = 0.34$, $p = 0.0001645$) but cloacal values were consistently higher than those recorded using the continuous monitoring system. This increase in temperature varied from 0.5 °C on D5–1.0 °C on D14.

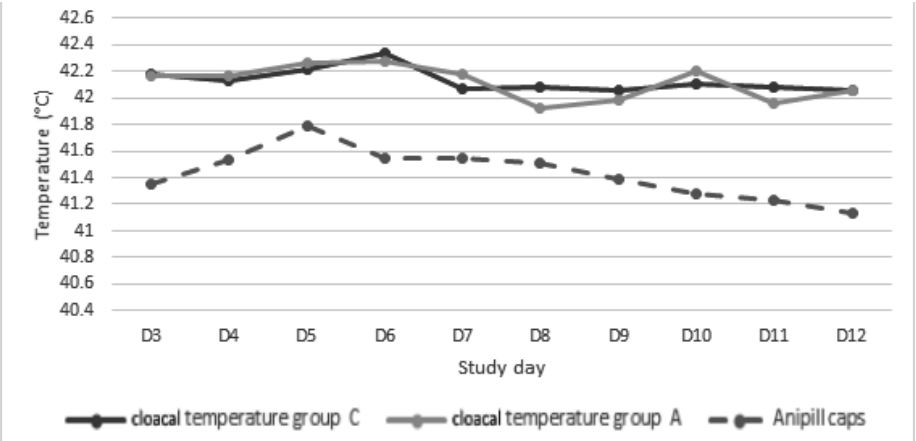

Figure 4. Mean cloacal temperature data in groups A and C as well as the mean temperature data in group A 15 minutes before taking the corresponding cloacal temperature

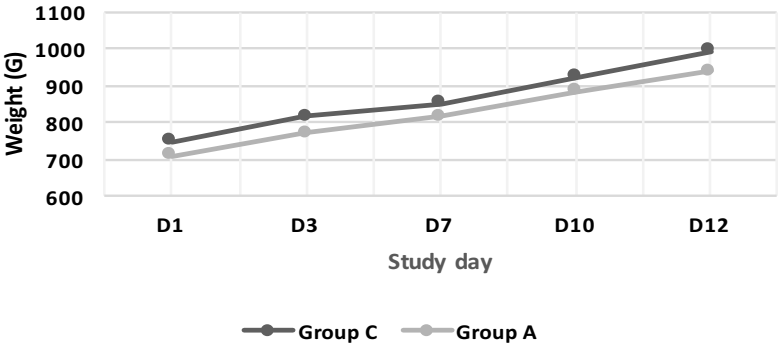

Figure 5. Mean weight of animals in group A (Anipill) and in group C (Control) over time

Figure 5 displays the profile of live weight over time in groups A and C. No significant difference was observed between groups ($p = 0.1787$). At placement of animals, on D0, there was a slight difference in live weight (+5.6% in group C) between the two groups. On D14 the same trend was observed (+5.6% in group C).

Challenge experiment

Data are shown in Figure 6. Following inoculation, none of the mock-infected chicken developed clinical signs. In the infected group, clinical signs were first observed two days post inoculation (dpi), peaked at three dpi (mean score: 1.6/3) and decreased to totally disappear by eight dpi. One bird was found dead at three dpi; on the same day, two birds were euthanized for ethical reasons as they displayed severe clinical signs (mortality of 27%, 3/11 birds). Upon necropsy, no specific lesion was observed on mock-infected birds while infected chickens displayed clear bursal atrophy: capsules were recovered and data were extracted for analysis. Data from two capsules were incomplete and were excluded from analysis.

Prior to inoculation, temperature follow-up revealed a similar trend for all birds, with a mean temperature of 41.2 °C, with lower values during the night and higher values during daytime. After inoculation, mock-infected chickens kept such a pattern of temperature

variation (gray line). Conversely, infected chickens (black line) showed a dramatic increase in temperature that was visible one dpi and reached a maximum at two dpi (maximum mean value: 43.4 °C) and progressively returned to normal values on five dpi. Extreme values were recorded with several chickens reaching temperatures above 44 °C and one bird peaking at 44.5 °C. Interestingly, the chickens that were euthanized due to severe clinical signs, although prostrated when euthanasia was decided, did not show hyperthermia at that precise moment, with respectively 40.9 °C and 39.6 °C of temperature.

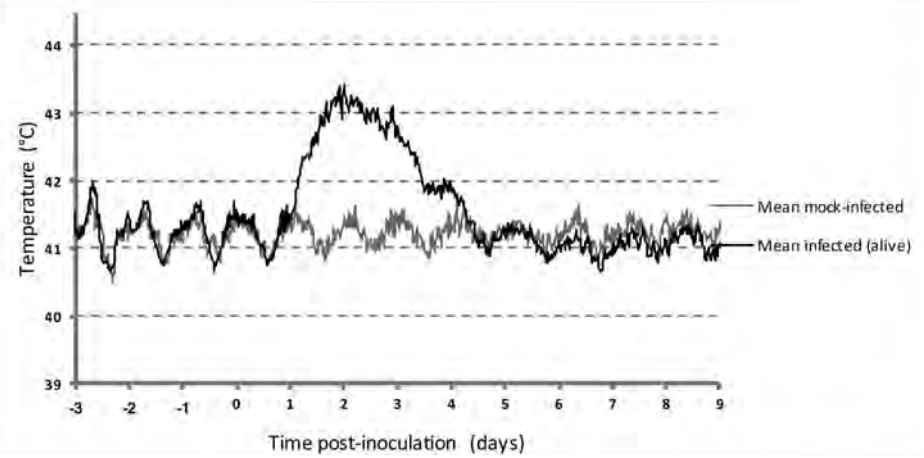

Figure 6. Average temperature values recovered by the capsules in mock-infected and infected animals before and after inoculation

Discussion

This study assessed the use of a telemetric sensor for the continuous monitoring of body temperature in chickens. The objectives of the experiments were first to test the safety of the system and then to evaluate its interest in animal infectiology research using inoculation by a very virulent chicken virus.

In natural conditions, chickens readily eat small stones. These stones, called grit, persist in the gizzard where they improve digestion by helping to grind coarse material such as seeds. We thus favored oral administration of the capsules rather than surgical implantation, as we anticipated ease of administration as absence of adverse effect in the animals.

Safety of the system was demonstrated under the conditions of our study. Oral administration was easily performed and no gizzard lesion was observed after implantation of the capsules during 14 days. For this study, the mean weight of animals was 727 ± 65 g (mean ± standard deviation). However, we already successfully and painlessly administered these capsules to chickens weighing about 300 g (unpublished data). Thus, this possibility extends the range of poultry species and size for which it is possible to implement the system.

Chickens that were given capsules had a similar growth rate compared with control chickens, further confirming the absence of any adverse effect of the system. Finally, cloacal temperatures were comparable for implanted and control chickens, arguing against any impact on body temperature due to capsule administration.

Even if cloacal and capsule temperatures were correlated, we found that cloacal temperatures values were consistently higher than those recorded by the capsules. This increase in temperature, ranging from 0.5 °C to 1.0 °C, likely reflected stress-induced

hyperthermia due to handling of the animals prior to cloacal temperature measurement. Increasing of the capsules sampling frequency (for instance to one measure every 30 seconds) and comparing cloacal with capsule temperatures at the exact time of cloacal temperature measurement would help to confirm the origin of this apparent discrepancy. Our results comply with those of Bae *et al.*, 2007, who reported a temperature rise from 0.6 °C to 0.7 °C in rodents after each procedure, when repeated measurements of body temperature were carried out. More generally, the wealth of data obtained by continuous temperature measurement may be of interest to evaluate stress and behaviour in the context of animal welfare studies, for instance, in combination with video recording.

Viral challenge experiment with a very virulent strain of IBDV further highlighted the interest of the system, this time in the context of infectious diseases experiments. Dramatic hyperthermia was observed in infected birds, which was concomitant with the onset of clinical signs. Continuous monitoring of body temperature provided a more sensitive, quantitative and objective information compared with clinical scoring. Interestingly, and maybe counter-intuitively, while all infected birds developed severe hyperthermia, the two chickens that displayed severe clinical signs, probably a few moments prior to death, had normal to low temperature. This subterminal hypothermia is in agreement with early descriptions of IBD (Cosgrove 1962) and argues against the idea that lethal fever would be responsible for the death of IBDV-infected animals. Such a drop in body temperature immediately before death, if confirmed, could be a useful parameter for ethical endpoint in animal experiments.

Conclusion

Under the conditions of our study, the telemetry system tested was safe for chickens and can be used to improve models in infectiology research for poultry.

References

Bae, D.D., Leon Brown, P., and Kiyatkin, E.A. (2007). Procedure of rectal temperature measurement affects brain, muscle, skin and body temperatures and modulates the effects of intravenous cocaine. *Brain Research* 1154, 61–70.

Chapon, P.A., Bessot, N., Gauthier, A., Besnard, S., and Moussay, S. (2012). Performance testing of an innovative telemetric temperature sensor in animals. *Journal of Thermal Biology,* 37: 255–259.

Clark, D.L., DeBow, S.B., Iseke, M.D., and Colbourne, F. (2003). Stress-induced fever after postischemic rectal temperature measurements in the gerbil. *Can Journal of Physiology and Pharmacology,* 81(9): 880–883.

Cosgrove, A.S. (1962). An Apparently New Disease of Chickens: Avian Nephrosis. *Avian Diseases* 6(3): 385–389.

Eterradossi, N., Picault, J.P., Drouin, P., Guittet, M., L'Hospitalier, R., Bennejean, G. (1992). Pathogenicity and preliminary antigenic characterization of six infectious bursal disease virus strains isolated in France from acute outbreaks. *Zentralbl. Veterinarmed. B* 39(9): 683–91.

Le Nouën, C., Toquin, D., Müller, H., Raue, R., Kean, K.M., Langlois, P., Cherbonnel, M. Eterradossi, N. (2012). Different domains of the RNA polymerase of infectious bursal disease virus contribute to virulence. *PLoS One* 7(1), e28064.

Kiyatkin, EA., and Brown, P.L. (2005). Brain and body temperature homeostasis during sodium pentobarbital anesthesia with and without body warming in rats. *Physiology and Behavior* 84, 563–570.

Pinheiro, J. (2018). nlme package version 3, 1-137, https://cran.r-project.org/web/packages/nlme/nlme.pdf.

Scudder, J.D., Blystone, R.V., and Pulliam, D.A. (2009). Control of anesthesia-induced hypothermia by ambient temperature regulation in rats. *Journal of Thermal Biology,* 34: 176–182.

Soubies, S.M., Courtillon, C., Abed, M., Amelot, M., Keita, A., Broadbent, A., Härtle, S., Kaspers, B., Eterradossi, N. (2018). Propagation and titration of infectious bursal disease virus, including non-cell-culture-adapted strains, using ex vivo-stimulated chicken bursal cells. *Avian Pathology* 47(2): 179–188.

Machine learning to realize phosphate equilibrium at field level in dairy farming

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Abstract

An important factor in circular agriculture is efficient application of animal manure. Therefore, input and output of nutrients, like phosphorus (P), need to be balanced. Currently, manure application is regulated with rather fixed P application norms as a generic translation of P yields of grassland and maize. Predicting P yields based on field specific, historical data could be an important step to better balance P input and output. This study's objective was to predict P yields based on field and weather data, using machine learning. The dataset contained 640 records of yearly crop yields per field between 1993–2016 with information on P input and output, irrigation, and soil status at field level as well as local weather data. Generalized boosted regression (GBR) was used to predict P yields for the last five years based on information from all previous years. Model performance was evaluated per year as well as together by plotting observed versus predicted values of all five years in one plot. This final plot was compared to a plot with the currently used generic application norms. Model performance per year showed that GBR could predict the trend from low to high rather well (correlations of ~0.8). Results of the five years together showed that GBR performance was better than the generic application norms (correlation 0.68 vs 0.59; RMSE 7.3 vs 8.2). In conclusion, GBR contributed to defining more flexible P application norms with the aim to realize a phosphate equilibrium.

Keywords: boosting, crop yield, machine learning, manure, phosphorus, regression tree

Introduction

Nutrient management is increasingly important in agriculture when public concerns about environmental issues and circularity are strong. An important factor in nutrient management on a dairy farm is the efficient use of animal manure for growing crops or grass, which means balancing inputs and outputs of nutrients. Current legislation concerning manure application is mainly focussed on phosphorus (P), and aims at realizing P equilibrium at field level with rather fixed P application norms. Legislation and control, however, focus on farm level, whereas for improving nutrient management, we need to scale down to field or even within field level. Predicting P yields based on field specific, historical data could be an important step to better balance P input and output. Models predicting future P yield may use information on fields, crops, soil parameters and open source weather data. Machine learning techniques can be useful in this respect, because they can be trained with many variables, without prior knowledge regarding their relationship or distribution function and with noisy data (Witten & Frank, 2005). This study's objective, therefore, is to predict P yields based on field and weather data, using machine learning before the first manure application.

Material and methods

Data sets

Data were available from the experimental dairy farm 'De Marke', located on a light sandy soil in the eastern part of the Netherlands. The dataset contained 640 records of yearly crop yields per field between 1993–2016, *i.e.*, 26–28 fields per year. Six fields were permanent grassland, while the majority of the fields were used in a rotational scheme. This scheme, in general, consisted of three years grassland, two years of maize and one year a cereal crop, although the number of subsequent years varied sometimes depending on the farm planning. Information was available on P input and output, irrigation, and soil status at field level as well as local weather data. Precipitation and temperature were measured at an on-farm weather station, whereas data on wind, sunshine, irradiation and evaporation were from the nearest weather station, located about 21 km east of the farm (KNMI, 2018). Mean daily temperature was 10 °C (ranging from -17 – 31 °C) and mean annual rainfall was 763 mm (ranging from 610–996 mm). Data were pre-processed to attain reasonable input variables and to reduce the number of weather variables from daily to monthly averages, five-day rolling averages and cumulative sums.

Model development and validation

Decision tree induction is one of the basic machine learning techniques and is, *e.g.*, robust against irrelevant input variables and is able to handle missing values (Friedman, 2001; Witten & Frank, 2005). To alleviate the main disadvantage of decision trees, namely its inaccuracy in prediction, we used the itterative method called boosting. Generalized boosted regression (GBR) using the Gradient Boosting Machine (h2o.gbm function (h2o version 3.20.0.2)) was applied to predict P yields for the last five years based on information from all previous years. Model performance was evaluated by plotting observed versus predicted values (Piñeiro *et al.*, 2008) per year, as well as together for all five years in one plot. This final plot was compared to a plot with the currently used generic application norms. The root-mean-square error (RMSE), coefficient of determination (R^2) and correlation coefficient (r) were used as performance metrics. Statistical significance of differences in performance were tested using a simple randomization test with 1,000 iterations for MSE, *i.e.*, the squared RMSE (Van der Voet, 1994) or using a t-test on Fisher's-z transformed correlation coefficients (or square root of R^2 values) (Cox, 2008). All analyses were performed in RStudio (version 1.1.423 running R version 3.5.0).

Results and Discussion

Yearly P yields ranged from 16–64 kg ha^{-1} (n = 393; 36.4 ± 7.9; mean ± SD) for grassland, 11–36 kg ha^{-1} (n = 202; 22.3 ± 4.7; mean ± SD) for maize and 18–43 kg ha^{-1} (n = 45; 28.3 ± 6.2; mean ± SD) for cereal crops for all years in the dataset. Grass yields were on average higher than crop yields, which corresponded well with the higher P application norms for grassland (80 kg P_2O_5 ha^{-1}, *i.e.*, 34.9 kg P ha^{-1}) compared to crop land (50 kg P_2O_5 ha^{-1}, *i.e.*, 21.8 kg P ha^{-1}). The year 2013, in general, had relatively low yields, whereas the year 2014 had relatively high yields. Those years were recognized as a 'bad' respectively a 'good' year for growing grass and crops by some of the co-authors and by a colleague of the experimental farm.

Table 1. Model performance (root-mean-square error (RMSE), coefficient of determination (R^2) and Pearson correlation coefficient (r)) of the models for 2012–2016 on validation datasets

Year	RMSE	R^2	r
2012	4.52	0.63	0.80
2013	7.61	-0.64	0.80
2014	10.35	0.26	0.80
2015	7.43	0.58	0.77
2016	5.09	0.63	0.82

Prediction performance on the validation data was rather good and constant when the correlation coefficient was considered (Table 1), indicating that the model was able to predict the trend from low to high yielding fields well in all years. The predicted levels, however, deviated stronger in the more deviant years 2013–2014 and the year thereafter, indicating that the model had difficulty with capturing the influence of year on P yields. Although weather information was included in the training of the model, weather of the coming growing season was considered to be not known at the moment of prediction, as the aim was to predict before the first manure application. Therefore, the model overestimated the P yields for 2013, the year with the more adverse weather circumstances, and underestimated the P yields for 2014. Futhermore, the model was probably not able to fully correct for these strong deviations in recent years, as performance for 2015 was worse than for 2012 and 2016 (Table 1).

When all five validation years were plotted together and compared to the legal application norms, it was shown that the GBM model performed better, both with respect to predicting the trend in observed P yields ($r = 0.68$ for the model compared to 0.59 for the application norms, $P < 0.001$) as with respect to predicting the exact levels ($R^2 = 0.46$ vs. 0.32 ($P < 0.001$) and RMSE = 7.33 vs. 8.22 ($P < 0.05$)). This proof of principle, however was based on a data from just one farm, which means, *e.g.*, one management and one soil type. The developed model, therefore, is not directly applicable on other farms and soil types. Development of a general applicable model requires detailed data from a range of farms from different regions with different soil types, which is currently not easily collected. When it becomes more common to apply precision farming technologies on dairy farms, like in-line manure or crop analysis sensors, and satellite or drone observations of fields, more data will become available to develop a more general applicable model.

Especially on grassland there are some clear opportunities to improve the model. Manure and artificial fertilizer are applied during the whole growing season and the model, therefore, could be adapted to within season prediction and management. In this way, more weather data and data on actual grassland usage, like mowing and grazing, and yields could be utilized. Another difficulty in the development of the model was that P yields from grazing could not be measured and are, therefore, based on calculations and assumptions. In this way the 'observed' values were not a real gold standard. When new ways of estimating grass growth and yields become available, the accuracy of the data could be improved.

Conclusions

This study has shown, as a proof of principle, that it is possible to predict P yields of individual fields before the first manure application reasonably well with a data driven method like GBM. These predicted P yields could be used to support decisions on manure application which are closer to the realized yields than the current legal manure application norms. A closer balance between P application and P yield helps to decrease losses and leads to a more circular agricultural system.

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References

Cox, N.J. (2008). Speaking Stata: Correlation with confidence, or Fisher's z revisited. *Stata Journal*, 8(3): 413–439.

Friedman, J.H. (2001). Greedy Function Approximation: A Gradient Boosting Machine. *The Annals of Statistics*, 29(5): 1189–1232.

KNMI (2018). *Daggegevens van het weer in Nederland (Daily weather data in the Netherlands)*. The Royal Netherlands Meteorological Institute (KNMI). https://www.knmi.nl/nederland-nu/klimatologie/daggegevens, date accessed: June 28th, 2018.

Piñeiro, G., Perelman, S., Guerschman, J.P., and Paruelo, J.M. (2008). How to evaluate models: Observed vs. predicted or predicted vs. observed? *Ecological Modelling*, 216(3-4), 316–322.

Van der Voet, H. (1994). Comparing the predictive accuracy of models using a simple randomization test. *Chemometrics and Intelligent Laboratory Systems*, 25(2): 313–323.

Witten, I.H., and Frank, E. (2005). *Data mining: practical machine learning tools and techniques*, Elsevier/Morgan Kaufmann, San Fransisco, CA.

A decision support system for energy use on dairy farms

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Abstract

This body of work pertained to the development and application of the Decision Support System for Energy use in Dairy Production (DSSED), an online portal offering decision support to dairy farmers wishing to invest in new farm infrastructure or upgrade their existing farm infrastructure. Increasing the utilisation of energy efficient and renewable technologies on dairy farms may increase the probability of Ireland achieving its strict EU targets by: 1) reducing electricity related CO_2 emissions on dairy farms, 2) reducing the required load from the electrical grid, and 3) increasing the proportion of renewable energy contributing to national electricity demand. However, such technologies may lead to greater long-term costs for dairy farmers if not managed and sized correctly. In order to provide useful advice, information such as dairy farm infrastructure details, management practices, available grant aid and electricity tariffs are required, as the impact of installing a particular technology may interact with existing on-farm technologies. Thus, the DSSED was developed to allow dairy farmers to calculate how a potential investment in a renewable or energy efficient technology will affect their economic and environmental sustainability, using input details specific to their current farm setup. The technologies which may be assessed include: plate coolers, variable speed drives, heat recovery systems, solar thermal water heating systems, solar photovoltaic systems and wind turbines. It is anticipated that the DSSED will be used extensively in the future to assist farmers, farm managers and policy makers with decisions pertaining to dairy farm energy, costs and CO_2 emissions.

Keywords: decision support; dairy energy; renewable energy; agricultural sustainability

Introduction

The dairy sector is Ireland's largest food and drink sector, representing a third (€4 billion) of overall export value in 2018, with export volumes of dairy products increasing by 5% in 2018 compared to 2017 (Bord Bía, 2019). Concurrently, Ireland produced 7.6 billion litres of milk in 2018, representing a 50% increase over 2007-09 levels, thereby achieving Ireland's 2020 milk production target of 7.5 billion litres, set out in 2010 (CSO (Central Statistics Office), 2019; DAFM, 2010).

The increased dairy herd, milk production and exportation of dairy products comes with its own significant challenges with regard to Ireland's 2020/2030 EU GHG targets, which aim to reduce GHG emissions by 30% by 2030, compared to 2005 levels (European Commission, 2016; Lanigan *et al.*, 2018). It is projected that with existing measures in place, Ireland's 2020 GHG emissions are set to be between 4–6% below 2005 levels, thus less than the targeted 20% reduction, with agricultural activities representing the largest sectoral share (EPA, 2017). This is representative of a projected increase in agricultural emissions by 4% to 5% by 2020 over 2015 levels, with an expected dairy cow herd increase of 7% being a contributing factor (EPA, 2017). As no immediate solution is available for reducing methane production from dairy cows, increasing the utilisation of energy efficient and renewable energy technologies in dairy production may serve as an appropriate measure to offset the projected increased GHG emissions. Moreover, effectively reducing the energy intensity of the milk production process may increase profits for dairy farmers as well

as reduce the magnitude of carbon credits required to ensure compliance with the 2030 climate and energy framework (European Union, 2014).

As the most energy intensive agricultural sector, research regarding energy use and environmental performance on Irish dairy farms has been extensive in recent years. The Model for Electricity Consumption on Dairy Farms (MECD) was developed by Upton *et al.* (2014), to simulate the electricity use and carbon emissions on dairy farms through mathematical equations. Breen *et al.* (2015) further developed the MECD model by integrating solar PV and wind turbine models. This allowed Breen *et al.* (2019) to develop a discrete infrastructure optimisation model for economic assessment on dairy farms (DIOMOND) to maximise the return on investment in dairy farm infrastructure (such as plate coolers, solar PV, etc.) on Irish dairy farms. Additionally, Murphy *et al.* (2013) developed a control system which varied the flow of ground water and ice chilled water in a dual stage plate cooler to minimise milk cooling related energy costs. Further comprehensive work in the Irish dairy domain has focused on applying machine-learning algorithms for forecasting milk production across different time horizons (Murphy *et al.*, 2015; Zhang *et al.*, 2016).

To help optimise the production of milk, some dairy farmers will look to purchasing new technologies such as solar PV, wind turbines and/or VSDs to reduce the cost of production. The implementation of these technologies has the dual impact of firstly, reducing the required load from the electrical grid, and secondly, increasing the penetration of renewable energy contributing to overall consumption, thus, improving Ireland's probability of achieving EU targets. However, such technologies may lead to greater long-term running costs for dairy farmers if not managed and sized correctly. Similarly, the impact of grant aid for these technologies may not be maximised without decision support infrastructure in place. Forecasted cost savings described by technology suppliers cannot be relied upon as these figures are typically calculated for the average dairy farm. For accurate calculations, information regarding details such as, specific dairy farm operations, available grant aid and electricity tariffs is required, as the impact of installing a particular technology may be greatly affected depending upon specific conditions. Without this information (i.e. making decisions based upon averaged/estimated payback periods calculated by the technology supplier), the cost savings of a particular technology may be greatly over-estimated, pro-longing the return on investment (ROI) period for farmers. This is of particular interest in the current volatile market whereby the average dairy farmer income declined by 22% in 2018 compared to 2017 (Bord Bía, 2019). Thus, this paper focused on the development and implementation of a Decision Support System for Energy use in Dairy Production (DSSED), offering a virtual environment whereby the cost and related GHG emissions associated with the installation of energy efficient and renewable technologies on Irish dairy farms can be assessed using state-of-art mathematical modelling. When utilised correctly, this will ensure ROI will remain as low as possible and ensure the long-term sustainability and growth of Ireland's dairy industry while helping to reduce the agricultural sector's contribution to overall GHG emissions, and improving Ireland's chances of achieving 2030 GHG emissions targets. More specifically, improving the energy efficiency, and increasing the penetration of renewable energy attributed to milk production directly aligns with the delivery of Ireland's National Energy Efficiency Action Plan (NEEAP) and National Renewable Energy Action Plan (NREAP).

Material and methods

Data Acquisition

Data were acquired through the automated recording of energy and water consumption through Teagasc, Moorepark (Cork, Ireland), the completion of a once-off farm infrastructure audit, monthly farmer input sheets, milk processor data and stock data from the Irish Cattle Breeding Federation (ICBF, 2016). These data were stored in the central

Teagasc Oracle database (Figure 1). In total, 58 Southern Irish pasture based dairy farms were monitored for inclusion in the database. Data collected from this cohort of Irish dairy farms has previously been utilised to conduct a statistical analysis of dairy farm energy and water consumption which informed the development of multiple linear regression and machine-learning models (Shine *et al.*, 2018a, 2018b, 2018c)the Irish government has targeted a 50% increase in milk production by 2020 over 2007–09 levels. Resulting milk price volatility and environmental constraints are forcing farmers to produce milk at lower costs with a lower overall environmental footprint. This entails using less energy and water resources to maintain commercial competitiveness and to reduce the environmental consequences of the production. This paper presents a detailed analysis of electricity and direct water consumption of 58 pasture-based, Irish commercial dairy farms. Data was acquired through a remote monitoring system installed on each farm in 2014 alongside corresponding milk production, stock, infrastructural and managerial data. The results derived from the analysis of this data allow key drivers of both electricity and water consumption to be understood with the ultimate aim of generating data to develop footprint models, to achieve a reduction in electricity and water use and to improve the cost efficiency of Irish pasture based dairy farms. The analysis showed electricity use of 39.84 Wh Lm–1and water use of 7.43 LwLm–1for the period Jan - Dec 2015. Dairy farm processes directly associated with milk production (milk harvesting and milk cooling. Currently, 20 dairy farms are recording sub-metered energy consumption allowing for the dynamic updating of consumption statistics and model parameters on a continuous basis.

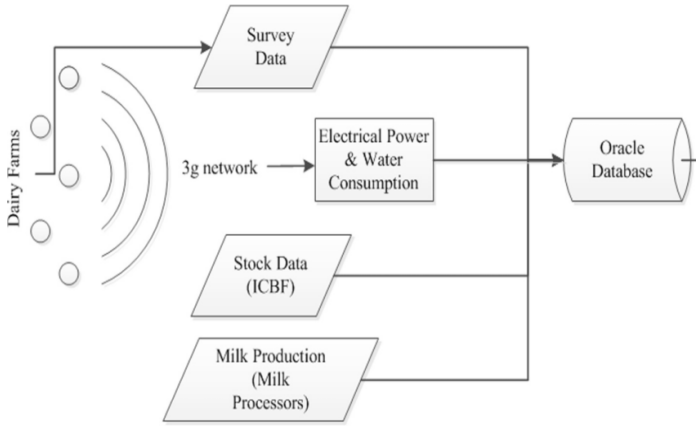

Figure 1. Acquisition of energy consumption, survey, stock and milk production data

Model for electricity consumption on dairy farms (MECD)

The model for electricity consumption on dairy farms (MECD), developed by Upton *et al.* (2014), was used to simulate the electricity consumption, related costs and CO_2 emissions on dairy farms under the headings of milk cooling, water heating, milking machine, water pumping, lighting and winter housing. Inputs to the MECD included details pertaining to the equipment on the farm such as milk cooling system, water heating system and milking machine. Information relating to the farm's herd such as number of cows and milk yield were also required, as well as specifics concerning the management of the farm including the milking times and frequency of on-farm milk collection.

In order to assess the feasibility of technology investments on dairy farms, a previously published dairy farm ROI model was used (Upton *et al.,* 2015). This model used average

farm financial performance data and variable and fixed cost data from the Teagasc Eprofit Monitor (Teagasc, 2017), as well as revenue from sales of both milk and livestock, with a base milk price set to 33 cents per litre. Farm variable costs were also included, such as feed, fertilizer, veterinary bills, contractors and electricity. The electricity costs were calculated using the MECD as described above. Fixed costs included hired labour, machinery, car/phone expenses and depreciation. All costs in the analysis were inflated by a certain amount (percentage) per annum. The financial performance of the farm before and after the addition of technologies, taking into account the capital costs of the technology in question, was then compared to assess the payback of these technologies. Further information on the modelling strategy can be found in Upton *et al.* (2015).

Technology Calculator

In order to develop a tool which allowed farmers to investigate whether investment in certain renewable and energy efficient technologies is economically viable, an intuitive user interface for existing models was developed to create the DSSED Technology Calculator (TC). The TC enables the user to enter details pertaining to a farm, including herd size, morning milking time, evening milking time, number of milking units, type of milk cooling system, type of water heating system, hot wash frequency, milk collection interval, whether the farm has a plate cooler, and the electricity tariff used. The user may then select from six different renewable and energy efficient technologies, with the user subsequently entering the size and cost of the technology as well as the level of grant aid associated with the technology and the rate of inflation. Information is then displayed relating to the payback period, CO_2 emissions, energy savings, renewable energy penetration and day/night time electricity use associated with the selected technology on the user's chosen farm. The six renewable and energy efficient technologies which may be chosen by the user, along with a brief explanation of each technology, are as follows:

- Plate cooler – Reduces milk cooling energy use by cooling milk using cold water in a plate heat exchanger, prior to the milk entering the main cooling system. As the use of a plate cooler may be simulated using the MECD, the development of a separate model was not required.
- Variable speed drive – This technology controls the speed of the milking machine vacuum pump motor in order to maintain the desired vacuum level for milking. VSDs can greatly reduce milking machine energy use. As the use of VSDs may be simulated using the MECD, the development of a separate model was not required.
- Heat recovery – These systems are installed in order to recycle the heat extracted from milk during cooling to preheat water for sanitation, thus reducing the energy used in water heating while also increasing the coefficient of performance of the milk cooling system. A mechanistic model was developed which used coefficients empirically derived from a series of experiments on the heat recovery system.
- Solar water heating – This renewable technology uses solar irradiance to heat a fluid as it is passed through solar panels. The fluid is then transferred from the panels through a coil in a water tank, transferring heat to the water before being passed through the solar panels once more. A mechanistic model was developed which used coefficients empirically derived from a series of experiments on the solar water heating system.
- Solar PV – These renewable systems use solar irradiance to produce electricity. This electricity may then be used on the farm as required, or exported to the grid if not needed. For simulation of solar PV system power output, the model previously described in Breen *et al.* (2015) was used.
- Wind turbine – This renewable technology converts wind power to electricity. This electricity may then be used on the farm as required, or exported to the grid if not

needed. For simulation of wind turbine power output, wind turbine power curve modelling was used. This involved the fitting of a polynomial curve to data provided by the wind turbine manufacturer, whereby the power output of the turbine could then be determined based on wind speeds. For more details on this method please refer to Breen *et al.* (2015).

Results and discussion

Energy Breakdown

The DSSED incorporates both graphical and numerical breakdowns of mean energy consumption, cost and carbon efficiencies (per litre of milk produced) according to each energy consuming process on a dairy farm. Energy consumption is reported in watt-hours per litre of milk (Wh L_m^{-1}), energy costs are reported in euro cent (cent) per litre of milk while carbon emissions are presented in grams of carbon dioxide (gCO_2) per litre of milk. When Cost is selected, users may analyse varying day and night rate electricity tariffs. A day rate electricity cost of 18 c/kWh and night rate cost of 9 c/kWh is set by default, in line with those from a standard Irish electricity provider (Electric Ireland, 2014). Day-time hours are fixed at 9am - 12 midnight. When Carbon Emissions is selected, users may analyse varying carbon intensity levels and the impact on $gCO_2\ L_m^{-1}$. A Carbon intensity level equalling 468 gCO_2/kWh is set as default in line with Ireland's carbon intensity level in 2015 (SEAI, 2016). A table is also presented containing numerical data related to efficiencies for each dairy farm process. With default parameters set, the DSSED database shows that in total, 41.1 Wh L_m^{-1} produced, equating to 0.60 cent/Lm and emitting 19.2 grams of $CO_2\ L_m^{-1}$. These values are in a similar range with (although may be considered more accurate due to larger timeframe) as the 39.8 Wh $L_m^{-1}$and 0.55 cent/Lm efficiency indicators calculated by Shine *et al.* (2018). The proportion of total energy consumption, cost and CO_2 related to each process is shown in Figure 2.

a) Energy Breakdown b) Cost Breakdown c) CO_2 Breakdown

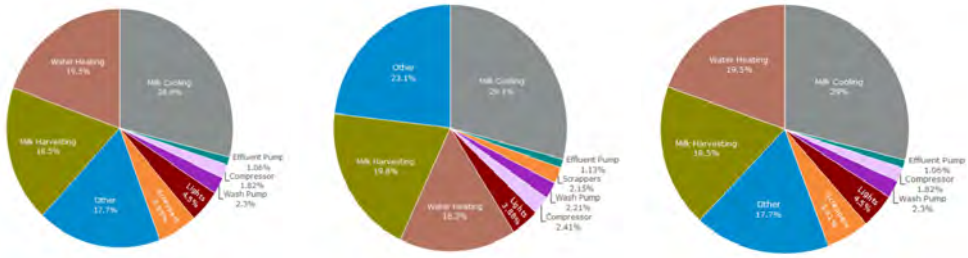

Figure 2. Pie charts presenting energy consumption (a) cost (b) and CO_2 emissions (c) breakdowns (downloaded from DSSED tool using default input parameters)

Figure 2a and Figure 2c show the breakdown of energy and CO_2, respectively. These figures have near identical data breakdowns due to the only difference in data being the carbon intensity figure. However, differences between percentage breakdowns shown in Figure 2a and Figure 2b, can be quite prevalent as cost is calculated using a day and night pricing structure, and thus is dependent upon the average daily usage trend of each energy consuming process e.g. heating hot water for the washing of parlour equipment etc. is responsible for 19.5% of total energy consumption. However, this equates to only 16.2% of total energy related costs. This is due to farms employing timers on their water heating systems to allow for the heating of water during cheaper night time hours. This has minimal impact on their usage of hot water, thus reducing the proportion of total costs attributed to water heating.

Technology Calculator Demonstration

The following scenario displays hypothetical results pertaining to the application of the TC when wishing to invest in Solar PV technology for a particular farm.

Table 1. Scenario farm setup and investment parameters

Farm setup		Investment conditions	
Herd size:	210 cows	Energy technology:	Solar PV
Milking times:	07:00 & 17:00	Solar PV size:	10 kWp
No. of milking units:	24	Investment cost:	€11,000
Cooling system type:	Direct expansion	Grant aid:	50%
Hz of hot wash:	Once per day	Inflation rate:	2%
Milk collection Hz*:	Every two days	Feed-in-tariff:	€0.18/kWh
Plate cooler (Y | N):	Yes	Household demand:	5,500kWh
Electricity tariff:	Daytime: €0.18/kWh Night time: €0.09/kWh		

* Hz = Frequency

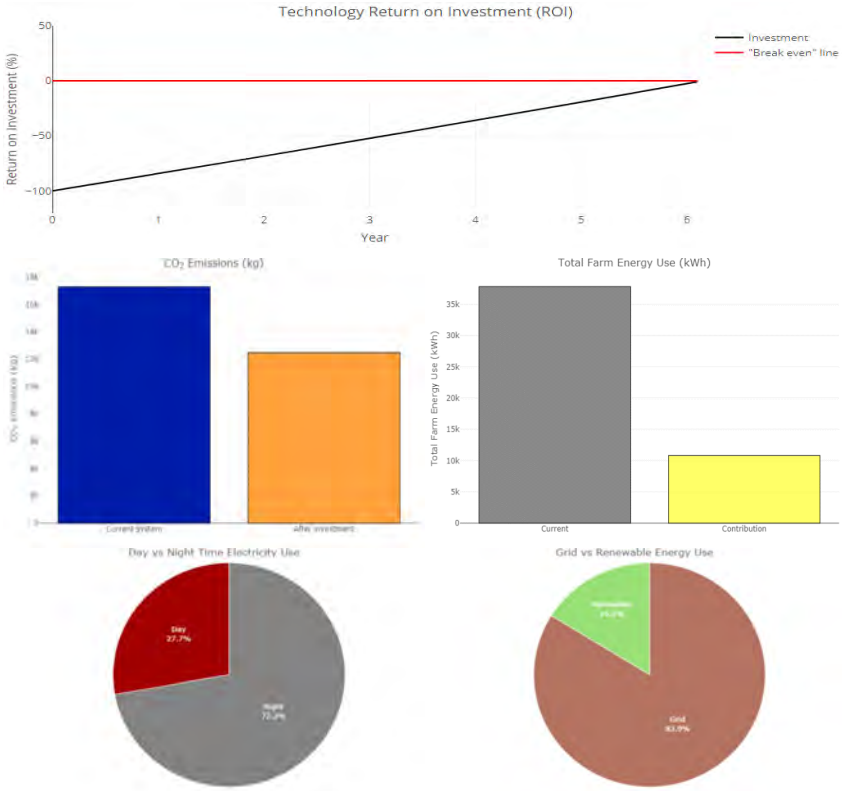

Figure 3. Showing graphical results from hypothetical scenario

As shown in Figure 3, the addition of a solar PV system under the conditions described saves 96,248 kg of CO_2 over its lifetime, offsets approximately 29% of the farm's total energy use, uses 16.1% renewable energy and 83.9% energy from the grid, uses 27.7% daytime and 72.3% night time electricity, and pays back within 6.1 years.

Conclusions

This paper detailed the methods by which the Decision Support System for Energy use in Dairy Production (DSSED) was developed, and demonstrated its usability. Both the statistical database and the technology calculator in DSSED are anticipated to be extremely useful to dairy farmers looking to expand their farms, as well as those looking to invest in renewable and energy efficient technologies. It is anticipated that the DSSED will be widely used in the future to aid farmers in making informed decisions. The information provided by DSSED is wide-ranging and will not only provide essential decision support, but also provide useful material for informing policy. Future work will extend the DSSED further by focusing on the optimization of dairy farm infrastructure investments, whereby the optimum combination of dairy farm equipment, management practices and electricity tariff will be found for a user-defined farm size, in terms of payback, CO_2 emissions and renewable energy penetration. Optimising dairy farm infrastructure investments is important since slight changes in equipment setup, management practices and electricity tariff can greatly affect the farm, both economically and environmentally. The optimisation of dairy farm infrastructure on a large number of farms could hypothetically save millions for the Irish dairy industry, and has the potential to considerably reduce CO_2 emissions.

Acknowledgements

We would firstly like to acknowledge the 58 farmers who took part in this study for their help and assistance in collecting essential electricity consumption data as well as the Irish Cattle Breeding Federation and Met Éireann for the sharing of stock and environmental data used in the development of this study. The Department of Agriculture, Food and the Marine (DAFM) and the Sustainable Energy Authority of Ireland (SEAI) supported this work.

References

Bord Bía. (2019). Export Performance & Prospects 2018–2019.

Breen, M., Murphy, M., Upton, J. (2015). Development and validation of photovoltaic and wind turbine models to assess the impacts of renewable generation on dairy farm electricity consumption. Breen, M Murphy, M.D. Upton, J. doi:10.13031/aim.20152189379.

Breen, M., Upton, J., Murphy, M.D. (2019). Development of a discrete infrastructure optimization model for economic assessment on dairy farms (DIOMOND). Comput. Electron. Agric. 156, 508–522. doi:10.1016/j.compag.2018.11.018.

CSO (Central Statistics Office). (2019). Milk Statistics December 2018 Available At: https://www.cso.ie/en/releasesandpublications/er/ms/milkstatisticsdecember2018/ (accessed 2.12.19).

DAFM (Department of Agriculture, Food and the Marine). (2010). Food harvest 2020 - A vision for Irish agri-food and fisheries. Available At: https://www.agriculture.gov.ie/ media/migration/foodindustrydevelopmenttrademarkets/agrifoodandtheeconomy/foodharvest2020/2020FoodHarvestExeSummary240810.pdf.

Electric Ireland. (2014). Energy Efficient Homes - All you need to know about the NightSaver Meter Available At: https://www.electricireland.ie/news-media/article/news/2014/05/21/all-you-need-to-know-about-the-nightsaver-meter (accessed 11.23.16).

EPA. (2017). EPA 2017 GHG Emission Projections Report Ireland's Greenhouse Gas Emission Projections EPA 2017 GHG Emission Projections Report Overview of Ireland's Greenhouse Gas Emission Projections Available At: http://www.epa.ie/pubs/reports/air/airemissions/ghgprojections/EPA_2017_GHG_Emission_Projections_Summary_Report.pdf.

European Commission. (2016). Energy Union and Climate Action: Driving Europe's transition to a low-carbon economy. Press Release.

European Union. (2014). A policy framework for climate and energy in the period from 2020–2030.

ICBF. (2016). Irish Cattle Breeding Federation Available At: http://www.icbf.com/ (accessed 8.18.16).

Lanigan, G., Donnellan, T., Hanrahan, K., Paul, C., Shalloo, L., Krol, D., Forrestal, P., Farrelly, N., O'Brien, D., Ryan, M., Murphy, P., Caslin, J., Spink, J., Finnan, J., Boland, A., Upton, J., Richards, K. (2018). An analysis of abatement potential of Greenhouse Gas emissions in Irish agriculture 2021-2030 Available At: https://www.teagasc.ie/media/website/publications/2018/An-Analysis-of-Abatement-Potential-of-Greenhouse-Gas-Emissions-in-Irish-Agriculture-2021–2030.pdf.

Murphy, M.D., O'Mahony, M.J., Upton, J. (2015). Comparison of control systems for the optimisation of ice storage in a dynamic real time electricity pricing environment. Appl. Energy 149, 392–403. doi:10.1016/j.apenergy.2015.03.006.

Murphy, M.D., Upton, J., O'Mahony, M.J. (2013). Rapid milk cooling control with varying water and energy consumption. Biosyst. Eng. 116, 15–22. doi:10.1016/j.biosystemseng.2013.05.007.

SEAI. (2016). Energy-Related Emissions in Ireland CO_2 Emissions from Fuel Combustion 2016 Report Energy-Related Emissions in Ireland Sustainable Energy Authority of Ireland.

Shine, P., Murphy, M.D., Upton, J., Scully, T. (2018a). Machine-learning algorithms for predicting on-farm direct water and electricity consumption on pasture based dairy farms. Comput. Electron. Agric. 150, 74–87. doi:10.1016/j.compag.2018.03.023.

Shine, P., Scully, T., Upton, J., Murphy, M.D. (2018b). Multiple linear regression modelling of on-farm direct water and electricity consumption on pasture based dairy farms. Comput. Electron. Agric. 148, 337–3. doi:10.1016/j.compag.2018.02.020.

Shine, P., Scully, T., Upton, J., Shalloo, L., Murphy, M.D. (2018c). Electricity & direct water consumption on Irish pasture based dairy farms: A statistical analysis. Appl. Energy 210, 529–537. doi:10.1016/j.apenergy.2017.07.029.

Teagasc. (2017). The Teagasc eProfit Monitor (€PM) Available At: https://www.teagasc.ie/rural-economy/farm-management/financial-analysis/farm-profit-analysis/the-teagasc-eprofit-monitor-pm/ (accessed 8.8.17).

Upton, J., Murphy, M., De Boer, I.J.M., Groot Koerkamp, P.W.G., Berentsen, P.B.M., Shalloo, L. (2015). Investment appraisal of technology innovations on dairy farm electricity consumption. *Journal of Dairy Science* 98, 898–909. doi:10.3168/jds.2014–8383.

Upton, J., Murphy, M., Shalloo, L., Groot Koerkamp, P.W.G., De Boer, I.J.M. (2014). A mechanistic model for electricity consumption on dairy farms: Definition, validation, and demonstration. *Journal of Dairy Science* 97, 4973–4984. doi:10.3168/jds.2014–8015.

Zhang, F., Murphy, M.D., Shalloo, L., Ruelle, E., Upton, J. (2016). An automatic model configuration and optimization system for milk production forecasting. Comput. Electron. Agric. 128, 100–111. doi:10.1016/j.compag.2016.08.016.

A methodology for daily analysis of AMS data providing herd characterisation and segmentation

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Abstract

The increasing amount of data collected in livestock farms thanks to PLF devices represents a huge potential of information to optimise animal husbandry and barn design. With particular reference to dairy cattle farming, Automatic Milking Systems (AMS) and the related devices and control software represent a highly informative source of cow-specific data. Such data can be translated into useful indications for management and design through algorithms able to provide a clear characterisation of the animal within the herd.

This study developed and tested a procedure for the comprehensive analysis of AMS-generated multi-variable time-series, with the following objectives:

- to define clusters of cows on the basis of daily values of their descriptive parameters analysed over a selected time period;
- to permanently monitor the time trend of the descriptive parameters of each cluster;
- to identify animals with anomalous scores with respect to the herd.

A commercial dairy cattle farm in the Po valley (Italy) was adopted as study case. A methodological approach based on hierarchical clustering has been formulated to best characterise each cow and identify cow clusters. The method proved suitable to identify clusters of cows clearly diversified in terms of parity, body mass, days in milk and daily milk yield, as well as individual outlier animals.

The results lend support to cow monitoring and to herd management optimisation. Future developments are represented by the integration of processing algorithms in PLF software.

Keywords: automatic milking system, cow-specific data, early warning, cow performance, animal monitoring

Introduction

The big amount of data collected in dairy cattle farms equipped with PLF devices represents a source of radical innovation in animal rearing. In fact, proper data processing approaches can lead to implement systems of early alert of anomalies in animal behaviour or performances with consequent increase in production efficiency and sustainability. In this regard, a study (Stangaferro *et al.*, 2016) was specifically devoted to analyse the trends of cows' rumination and activity scores in relation to clinical diagnosis in order to identify patterns of these variables with forecasting potential, particularly for what concerns metritis. The increasing adoption of Automatic Milking Systems (AMS) in dairy cattle farms has been continuously providing cow-specific data to farmers with time frequency greater than once a day. The impact of adopting AMS on farms with regards to changes in milking labor management, milk production and milk quality was documented in literature (Tse *et al.*, 2018). A cluster-graph approach was developed and tested to datasets collected in Italy by automatic milking systems and containing real-time information for each cow (Bonora *et al.*, 2017). In this regards, a research (Adamczyk *et al.*, 2017) assessed the effectiveness of cluster analysis to analyse the physical activity of dairy cows milked with AMS, taking into account environmental conditions. The validity of the clustering

approach was confirmed by further insights (Bonora *et al.*, 2018) and the literature review revealed that defining optimal processing methodologies to extract information from AMS-generated data appears a topical issue in the field of PLF innovation.

The goal of this study was to define a data processing procedure for dairy farms equipped with automatic milking systems, suitable to define subgroups of the herd characterised by common values of the parameters describing the cows conditions, as well as to identify outlier animals characterised by anomalous trends of any parameter.

Material and methods

Study case

An Italian dairy farm with ordinary productive characteristics, equipped with AMS, was adopted as the study case for data collection, test of the methodology developed, and interpretation of the results. The study case farm was located in the municipality of Ghedi, province of Brescia, Lombardy Region, Italy (WGS84 coordinates 45°24'07.2"N 10°16'49.08"E), equipped with an automatic milking system (AMS) by Lely (Maassluis, The Netherlands), model Astronaut 4, and hosted around 90 Friesian cows. The barn hosting the lactating and dried cows was a 42 m long and 17 m wide rectangular building with steel frame structure and double pitched roof of insulated metal panels with gutter heights of 5 m, 20% slope and ridge opening. The barn, whose longitudinal axis had 71° azimuth orientation, consisted of a feeding area and an external feed delivery lane on the southern side and a resting area in the northern part of the building, with two head-to-head rows of cubicles. The barn had concrete floor with scrapers. The AMS was located on the western side and beyond it there were the milk-room, the control office and a technical plant room. Ventilation was controlled by four high volume low speed (HVLS) fans with five horizontal blades which were activated by a temperature-humidity sensor. The milking robot was programmed to assure a number of daily visits for each cow depending on the cow productivity and its expected optimal milk yield per visit, with a minimum of two and a maximum of four daily visits as constraints. The analyses performed are referred to the study period from 7–22 July 2016, with multiple time intervals illustrated below. The average number of daily milking events in that period was 2.7 and the average number of daily milking refusals of the AMS system was 1.3. The average daily milk production per cow was 39.4 liters and the average of the daily supplementary feeding delivered to lactating cows was 3.8 kg.

Time frames

This study was targeted to the short-time trends of the main parameters usually available in farms equipped with AMS, connected to production and animal behaviour, with the specific aim of finding anomalies. Previous researches about cows clustering showed that a long study period such as three months is suitable to achieve a steady subdivision of the herd with the identification of the main performance potentials of the individual cows (Bonora *et al.*, 2018). At the same time this approach was not suitable to account for the variation in animal conditions that can occur in shorter periods. A further study underlined that cow clusters developed on monthly basis revealed changes in cluster arrangement in the different time frames (Bonora *et al.*, 2017). At the same time, data analyses performed over several dairy farms (Bonora, 2018) pointed out that the descriptive variables of animal performances and conditions showed significant daily oscillations and trends that could appear clear and comparable on a weekly basis. For this reason, the analysis methodology was defined to be implemented in time intervals of eight days, considered suitable to identify groups with similar trends in time and at the same time to update dynamically the results. The time intervals were meant to be reconsidered daily, with the identification of the period of the eight previous days as the reference for the analysis, so that the famer

can have an up-to-date picture of the conditions of its herd, besides the time series of all the previous conditions. This work presents the analyses referred to three eight-day time intervals shifted four days from one another, in order to study the clusters composition and the respective features, besides their evolution in time.

Clustering methodology

The variables for the implementation of the clustering procedure among the parameters available describing each cow's behavior and health conditions were selected as follows: daily average of the activity score (recorded by electronic collars); daily average of rumination time (minutes, recorded by electronic microphones); days in milk; daily average milk temperature (°C); daily average cow body mass (kg); daily average milk conductivity (cS/m); parity (#). The data about milking and milk properties were recorded by the AMS.

The variables expressing milk productivity, such as daily number of milkings and milk yield, were not selected as parameters for clustering because they were considered as dependent variables according to which the effectiveness of the clustering procedure and the productive feature of each resulting group of cows were assessed.

On the basis of the study aims, a hierarchical clustering was selected as the methodological approach. It was preferred to the alternative clustering algorithms based on *k*-means approach because neither it requires a starting point, nor it calls for an aprioristic definition of the number of subgroups. In fact, the final output of a hierarchical clustering is not a unique clustering arrangement, but a dendrogram, i.e. a multilevel 'tree', so that the level of grouping may be specific for each process, depending on conditions that can be stated on the basis of the study objectives.

The hierarchical clustering was achieved by developing the following phases:

I *Distance*. The differences among every pair of cows were calculated in terms of Euclidean distance on all the variables considered, expressed in terms of z-scored values. The output of this first phase was a symmetric distance matrix;

II *Linkage*. First, the algorithm joined the two animals with the smallest distance calculated in Phase 1. Then the distance matrix was recomputed using the newly formed cluster instead of the two individual cows. The procedure was iterated until a complete hierarchical tree was formed and all the cows were connected. In particular, the Unweighted Pair Group Method with Arithmetic Mean (UPGMA) was selected to compute the distance between two clusters: the distance d(C,E) between two clusters C = A U B and E is equal to:

$$d(C,E) = \frac{|A|*d(A,E) + |B|*d(B,E)}{|C|} \quad (1)$$

where $|X|$ represents the cardinality of the generic set X and d is the Euclidean distance;

III *Cut*. In the third phase, the method to decide where to cut the tree was chosen, i.e. which level of the dendrogram had to be selected to identify different groups. The starting selection consisted in the identification of simply two clusters corresponding to the last linkage. Then, the two found clusters were tested against the conditions stated below:

- "No Small size" (S) condition. If the size of one found cluster was less than or equal to 2, the one or two cows identified were considered outliers: they were removed from the herd data and separately analysed. In this case, the 'new' herd (i.e. without the outliers) restarted from point II: linkage phase;
- "No Big size" (B) condition. If the size of one found cluster was greater than 60% of the herd, it was translated into the possibility to deepen the analysis. In this case,

the procedure restarted from the Phase III increasing the number of clusters by one unit and the two conditions were verified again on the new clusters obtained.

The process stopped when both conditions were verified, which means that the subdivision of the herd into clusters represented a trade-off between size and dissimilarity which was considered functional to the study aims.

IV *Analysis*. The last step was diversified depending on the presence or absence of outliers, as follows:

a. *Presence of outliers* (i.e. at least one outlier cow detected). If some outliers were found by the S condition, the distances between all the z-scored parameters of this cow and all the remaining ones in the herd were calculated within the time period selected for the analysis. The maximum distance represented the parameter with the greatest effect for the definition of the outlier. Then the analysis went on as in the case without outliers (see point b).

b. *Herd without outliers*. After the identification of the best subdivision of the animals into clusters, the trends of the clustering parameters and the other significant variables available in the selected time period were plotted and analysed.

The software selected for the development and processing of the algorithm is MATLAB R2018b (Mathworks, 2018). The above procedure is meant to be repeated every day adopting the previous eight days as the reference period, thus providing the farmer with an up-to-date perspective of the conditions of the animals and the respective trends.

Results and discussion

The algorithm developed is suitable to run with every time period length, and in this study the eight-day format was identified as the best solution, as it was mentioned above. The analysis method was tested with reference to several study periods and, on the basis of the preliminary results, the time frame from 7 July 2016–22 July 2016 was selected as a study case to be reported, as it involves all the methodological phases identified and represents a useful example to show all the steps provided for the algorithm formulated. Three eight-day intervals were analysed within this period 7-14, 11-18, 15-22 July, respectively referred to as *f* (first), *s* (second), *t* (third) period. In this time interval, the total number of milking cows reared - and thus analysed - ranged between 59–63. The clustering procedure led to identifying two clusters in the first and second periods, while three clusters in the third one. Figure 1 shows the results of the iterations which led to the definition of the clusters. In the first period, two iterations were necessary to identify three outliers meeting the S condition after the Phases I, II and III (one in the first iteration and two in the second one), then after one more iteration, B condition was also met. In the second period, the outlier was found after the first iteration, then the clusters were defined after the second one. In the third period, the procedure identified the outlier, then the procedure came back to the linkage phase and the algorithm identified two clusters. In this case, the B condition was not met: the bigger cluster was composed by more than 60% of the herd, so the algorithm came back to the 'Cut phase' increasing the number of clusters and bringing it to three, thus defining the final grouping for this time period. Therefore in all the three periods there is no cluster with greater size than 60% of the herd and there is no cluster composed by less than three animals.

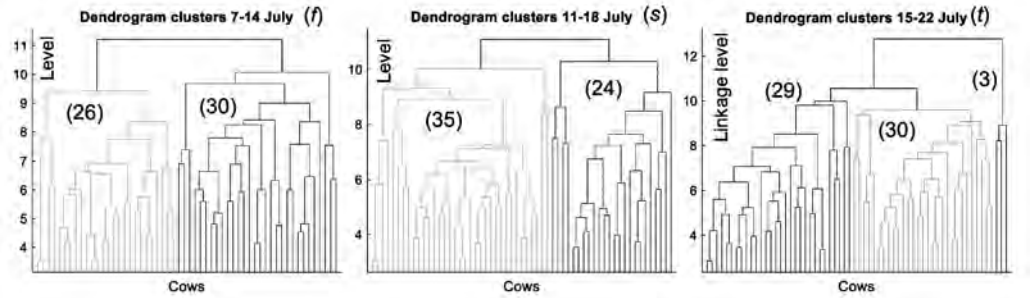

Figure 1. Dendrograms resulted from the last iteration, where the clusters were identified per each period; cluster cardinalities in brackets.

After the formulation of the final clusters, the algorithm analysed the characteristics of the found groups: this step is useful to monitor the trend of the herd for what concerns the most common variables measured in a modern barn. All the variable monitored were thus analysed to identify the features characterising each cluster. Firstly, a clear diversification among clusters was recognised in terms of parity and days in milk, as it is shown in Table 1: one cluster in each period, specifically 1(*f*), 1(*s*), 2(*t*), mainly included primiparous cows; clusters 2(*f*), 2(*s*), 1(*t*) included mainly the animals in third lactation; in the third period a further Cluster 3(*t*) was identified, mainly composed by cows with five lactations. Moreover, Clusters 1(*f*), 1(*s*), 2(*t*) mainly included cows in the first part of lactation, while Clusters 2(*f*), 2(*s*), 1(*t*) concerned the final stage of lactation and Cluster 3(*t*) about the third quarter of lactation period.

Table 1. Parity and days in milk values in clusters (average ± standard deviation)

	Cluster	7-14 July (*f*)	11-18 July (*s*)	15-22 July (*t*)
Parity	1(*f*), 1(*s*), 2(*t*)	1.27±0.45	1.57±0.85	1.53±0.5
	2(*f*), 2(*s*), 1(*t*)	3.3±1.1	3.58±1.35	3.07±1.16
	3(*t*)	-	-	5.67±0.58
Days in Milk*	1(*f*), 1(*s*), 2(*t*)	105±73	108±83	103±81
	2(*f*), 2(*s*), 1(*t*)	217±99	242±71	236±88
	3(*t*)	-	-	198±46

* At the beginning of the time period

The parity condition was clearly confirmed by the body mass values: cows of Clusters 1(*f*), 1(*s*) and 2(*t*) had masses on average over 100 kg smaller than the rest of the herd. Clusters 1(*f*), 1(*s*) and 2(*t*) were also characterised by a clearly higher activity score, while cluster 3(*t*) had the minimum one.

Then the average daily number of milking events was analysed (Figure 2), showing that younger cows of Clusters 1(*f*), 1(*s*) and 2(*t*), steadily went to the AMS more often (about three) than older cows of clusters 2(*f*), 2(*s*) and 1(*t*), who expressed about 2.5 milkings per day. This relationship was confirmed by the trend of Cluster 3, composed by the oldest cows, which expressed the minimum number of daily visits to AMS.

Figure 2 shows that productions of Clusters 1(*f*), 1(*s*) and 2(t) were almost always neatly

higher than Clusters 2(*f*), 2(*s*) and 1(t), respectively. This was likely due to the different days in milk, as cows of Clusters 1(*f*), 1(*s*) and 2(t) were mainly in the lactation peak period. Cluster 3 did not reveal a particularly lower milk yield (38.1 l), although it was composed by old animal beyond the production peak.

The model can be also used to compare the parameters of the outlier cows and the average parameters of clusters with particular reference to the variables marked in the step of outlier identification as mostly significant. The three outliers detected in the first periods expressed anomalous values respectively of days in milk conductivity (and activity. The first case (492 days in milk at the beginning of the period) was clearly due to abortion, the second case highlighted anomalous high values of conductivity in comparison to the herd, and it can be interpreted as an early warning of mastitis risk. The third case was referred to a 6th parity cow and pointed out activity scores within the same range of Cluster 2, but with a different distribution within the period. In the second period the outlier was due to her activity score, with a peak at the beginning of the period, which is compatible with possible heat, as the cows had 67 days in milk. In the third period the outlier expressed high conductivity in comparison with the three clusters, thus calling for attention to animal's health.

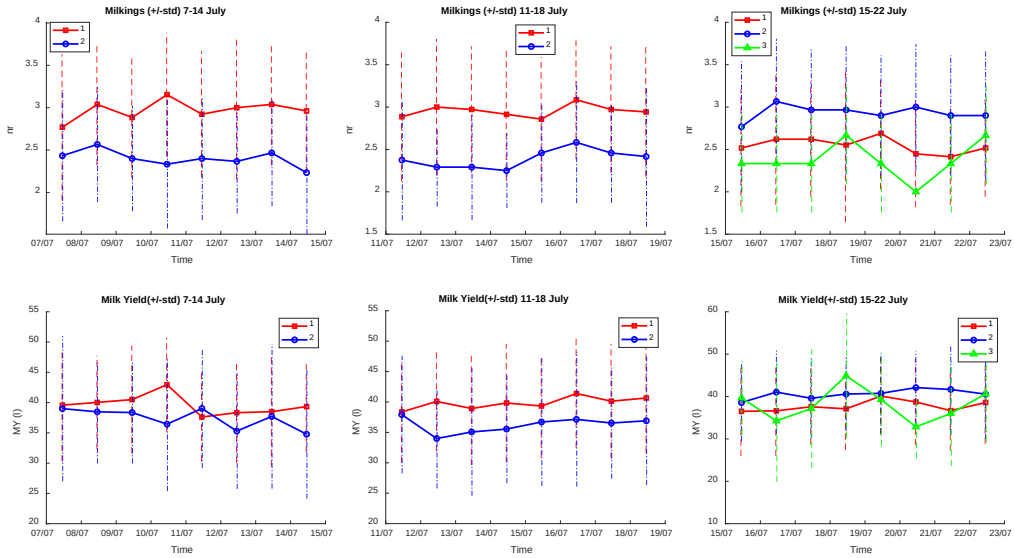

Figure 2. Trends of average number of daily milkings and milk yield in the clusters (association between colours and cluster numbers reported in labels)

Conclusions

The study led to the development of a data processing method suitable for dairy farms equipped with automatic milking systems, capable of defining subgroups of the herd characterised by common short-term trends of the parameters describing the health and production conditions, as well as identifying outlier animals.

The method was tested over a study case and it proved suitable to be adopted by farmers as a tool to enhance the informative content of the huge amount of data made available by the adoption of PLF tools, such as milking robots and related devices. In particular, the method proved suitable to identify outlier cows with production and health parameters significantly different from average herd values.

The analyses performed are meant to be repeated every day, with the same time frame length. In this way it is possible to provide the farmer with a vision of the condition of the herd in the last week, with the identification of possible anomalous cows. At the same time, the results are meant to be recorded, thus constituting the time history of the herd. This system allows to have an immediate representation of the trends of the parameters, which can be in-depth analysed with reference to individual cows.

This system represents a preliminary early warning for the animals identified as outliers, which should be closely monitored to understand the reasons of the anomalies. In case health issues were the cause of the anomalies, this procedure clearly provides an advantage in treating the problematic cows early. The method also allows cow clusters within the herd to be recognised, thus providing the farmer with a knowledge framework about the main features of the groups. In this way, it is possible to better understand performances and behaviours of individual cows, comparing them with the parameters describing the respective cluster.

Future developments of the research include the combined analysis of clustering results with the trends of environmental data, to better identify their effects on the animals, with reference to the various features detected in clusters and outliers. The integration of the methodology proposed with the cluster-graph approach already developed could also enhance the effectiveness of the representation of the clustering results.

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References

Adamczyk, K., Cywicka, D., Herbut, P. and Trześniowska, E. (2017). 'The application of cluster analysis methods in assessment of daily physical activity of dairy cows milked in the Voluntary Milking System', *Computers and Electronics in Agriculture*, 141, pp. 65–72. doi: 10.1016/j.compag.2017.07.007.

Bonora, F. (2018). *Numerical modeling for PLF in dairy cattle farms: methods for the analysis of environmental, productive and behavioral parameters*. University of Bologna.

Bonora, F., Benni, S., Barbaresi, A., Tassinari, P. and Torreggiani, D. (2018). 'A cluster-graph model for herd characterisation in dairy farms equipped with an automatic milking system', *Biosystems Engineering*, 167. doi: 10.1016/j.biosystemseng.2017.12.007.

Bonora, F., Tassinari, P., Torreggiani, D. and Benni, S. (2017). 'An innovative mathematical approach for a highly informative treatment of automatic milking system datasets: development and testing of enhanced clustering models', in 8th *European Conference on Precision Livestock Farming, Nantes (F), 12-14 September 2017*, pp. 692–700.

Mathworks (2018). *Primer (R2018b)*.

Stangaferro, M.L., Wijma, R., Caixeta, L.S., Al-Abri, M.A. and Giordano, J.O. (2016). 'Use of rumination and activity monitoring for the identification of dairy cows with health disorders: Part III. Metritis', *Journal of Dairy Science*. Elsevier, 99(9): pp. 7422–7433. doi: 10.3168/jds.2016–11352.

Tse, C., Barkema, H.W., DeVries, T.J., Rushen, J. and Pajor, E.A. (2018). 'Impact of automatic milking systems on dairy cattle producers' reports of milking labour management, milk production and milk quality', *Animal*. doi: 10.1017/S1751731118000654.

Session 2

Precision Livestock Farming Technology for Sheep

Relationship between accelerometer features and behavioural traits in Sarda dairy sheep submitted to short term grazing test

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Abstract

The accurate estimation of herbage intake is key to adequately feed grazing ruminants. Ten dairy Sarda sheep fitted with a halter equipped with an accelerometer (BEHARUM device) were allowed to graze for six minutes on micro-swards of Italian ryegrass (*Lolium multiflorum* L.), alfalfa (*Medicago sativa* L.), oat (*Avena sativa* L.), chicory (*Cichorium intibus* L.) and a mixture (Italian ryegrass and alfalfa). Accelerometer data and video recordings of behaviour were collected simultaneously. The raw acceleration data was processed to calculate 15 variables: mean, variance and inverse coefficient of variation (ICV; mean/standard deviation) for the X, Y and Z axis and the resultant. A database was then created inclusive of the acceleration variables and herbage intake (DMI, g), intake rate (DMIR, g/minute), bite mass (DMBM, g) on a DM basis, and the logarithm of number of bites (LB) measured during the tests. Partial least square regression analysis (PLSR) was used to verify if the acceleration variables could be used as predictors of behavioural traits. The precision and accuracy of PLSR were evaluated implementing the Model Evaluation System, in which predicted values were regressed against observed ones, based on R^2, RMSEP and Dent & Blackie test. The PLSR showed an overall good accuracy (Dent & Blackie test $P = 1$) and was proven precise for the estimation of LB ($R^2 = 0.86$, $RMSEP = 3\%$), DMI and DMIR ($R^2 = 0.71$, $RMSEP = 22\%$), but not of DMBM ($R^2 = 0.32$, $RMSEP = 26\%$). To conclude, BEHARUM can accurately estimate with high to moderate precision number of bites and herbage intake of sheep short term grazing Mediterranean forages.

Keywords: accelerometer, PLSR, bites, herbage intake

Introduction

Studying the feeding behaviour of ruminants and monitoring the energy intake during grazing is of fundamental importance to improve feeding efficiency, animal productivity and pastures management, respecting environment and animal welfare (Blomberg, 2011; Oudshoorn *et al.*, 2013; Swain & Friend, 2013). The productivity of grazing animals depends indeed on feed intake, which is a difficult measurement, particularly for long periods (Milone *et al.*, 2012). Jaw movements are of great importance to assess animal grazing strategies when grazing in different types of pastures and to better estimate their intake (Andriamandroso *et al.*, 2016). Several techniques have been developed to monitor animal jaw movements and to detect bites that are the elementary components of the grazing process (Ungar *et al.*, 2006a; Andriamandroso *et al.*, 2016). Accelerometer sensors have been tested to automatically count jaw movements (Umemura *et al.*, 2009; Oudshoorn *et al.*, 2013; Rombach *et al.*, 2018) however, as for sound sensors, the sensitivity of accelerometers could provide interferences and undesirable signals during recording sessions, therefore significant developments are required in order to isolate the signal relative to the jaw movements of grazing animals (Andriamandroso *et al.*, 2016).

The objective of this study was to derive a model to predict sheep behavioural variables as number of bites, bite mass, intake and intake rate, on the basis of variables calculated from acceleration data recorded by a customised tri-axial accelerometer based sensor named BEHARUM.

Material and methods

Forage species

Five treatments, four monocultures and one mixture, established by sowing in paired boxes the forage species to create micro-swards (Orr *et al.*, 2005) were compared. The monocultures were: Italian ryegrass (*Lolium multiflorum* L.), alfalfa (*Medicago sativa* L.), oat (*Avena Sativa* L.) and chicory (*Cichorium intibus* L.); the mixture was constituted by Italian ryegrass and alfalfa.

Experimental design

Two replicate groups of five animals each of Sarda lactating ewes, homogeneous for age (4 ± 1.5 years, means ± SE), body weight (43.68 ± 3.07 kg), body condition score (2.65 ± 0.19), stage of lactation (104 ± 9 DIM) and milk production (1.270 ± 0.04 kg) were used for the micro-swards test. Each treatment was offered to each ewe in a 5 × 5 Latin-Square with two replicates in a five day period. Within each replicate, the five experimental animals were submitted to the treatments in succession. The order in which the tests were conducted was randomised within each experimental day.

Measurements

Animals were worn with the BEHARUM device (Giovanetti *et al.*, 2017) and each treatment was offered to each subject (Figure 1) in a rack for six minutes (test). The behaviour of each experimental animal was recorded by a fixed camera (eating time and number of prehension bites) during the test. The micro-sward boxes were weighed before and after each test with an accuracy of 0.5 g in order to determine the biomass removed. The following traits were calculated: dry matter herbage intake (g) and intake rate (DMI, DMIR, respectively); number of bites recorded during the test; dry matter bite mass (DMBM, g) calculated dividing the DM weight changes of the microswards, corrected for evapotranspiration losses, by the number of bites.

Figure 1. Sheep during the test

Preliminary data processing

Video recordings were coded manually counting the total number of bites taken by each animal during the test. The number of bites was transformed in logarithm (LB), in order to obtain a normal distribution of the variable.

Mean (MX, MY, MZ), variance (VX, VY, VZ), sum (SX, SY, SZ), inverse coefficient of variation (i.e. mean/standard deviation, ICVX, ICVY, ICVZ) of acceleration data for each axis, as well as the resultant mean (MRES), variance (VRES) and inverse coefficient of variation (ICVRES)

values of the three axes (Watanabe *et al.*, 2008), were calculated for the total eating time. A dataset was then created including the behavioural traits (LB, DMI, DMIR, DMBM) and the above mentioned acceleration variables calculated for the total eating time of feeding, for a total of 19 (number of variables) per 70 (number of record) dataset.

Statistical analyses

Degression analyses were performed to see if the acceleration variables (MX, MY, MZ, VX, VY, VZ, SX, SY, SZ, ICVX, ICVY, ICVZ, MRES, VRES, ICVRES) can be used as explanatory variables of the response variables (DMI, DMIR, DMBM and LB).

For this scope, the partial least square regression (PLSR) model was used (Dimauro *et al.*, 2011).

The general structure of the model is:

$$Y = XB + E \quad (1)$$

where Y is an n x m response matrix, X is an n x p design matrix, B is an n x m regression coefficient matrix, and E is an n x m error term.

To validate the model a leave-one-out cross-validation has been used. The root-mean-square error of prediction (RMSEP) was used to assess the prediction ability of PLSR. Finally, the precision and accuracy of the model were assessed implementing the Model Evaluation System (MES, release 3.1.16, Tedeschi, 2006) in which the predicted values were regressed against the observed ones. The model evaluation was based on Dent and Blackie test and R^2.

Results and discussion

The aim of this work was to derive a model to predict sheep behavioural variables related with intake on the basis of calculated accelerometer variables.

Results of the adequacy of predictions of PLSR procedure are reported in Table 1. As demonstrated by the Dent and Blackie Test ($P > 0.05$), this procedure was able to provide accurate estimates, that is how closely model-predicted values are to the true values of the predicted values for all variables listed. This means that equation parameters, the intercept and slope, were contemporarily not significantly different from 0 and 1, thus indicating that all the equations pass through the origin and the intercept is equal to zero.

Table 1. Results of Model Evaluation System (MES)

Y	Adjusted R2	Dent and Blackie test P<	RMSEP (%)
LB	*0.86*	*0.88*	*3.3*
DMI (g)	*0.71*	*1.0*	*22.2*
DMBM (g)	*0.32*	*1.0*	*26.4*
DMIR (g min^{-1})	*0.71*	*1.0*	*22.1*

LB=logarithm of number of bites; DMI=dry matter intake; DMBM=dry matter bite mass; DMIR=dry matter intake rate

Plots of the regression equations among predicted and observed values are shown in Figure 2. The degree of precision of the model that indicate the model's ability to predict similar values consistently, was pretty good although it varied according to the variable considered. The prediction of the number of bites, expressed as logarithm (LB) reported the highest adjusted R^2 followed by DMI and DMIR variables while DMBM has the lowest

R^2 value. The RMSEP was very low when the number of bites were predicted while it grew up for the other variables, especially for DMBM.

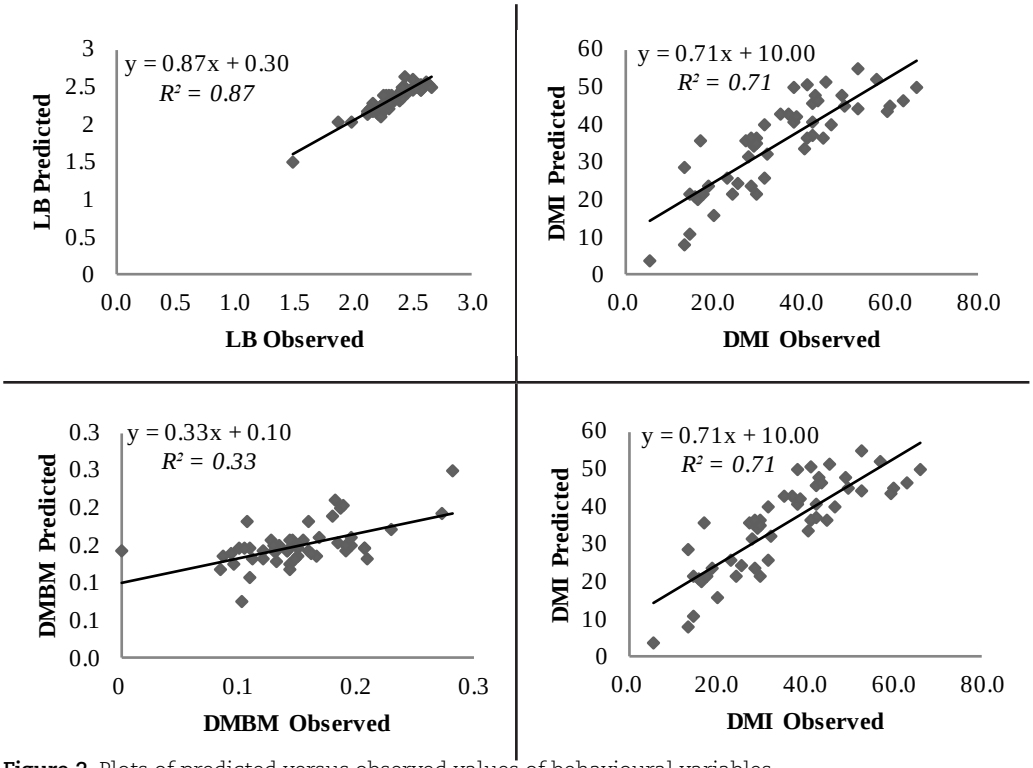

Figure 2. Plots of predicted versus observed values of behavioural variables

LB = logarithm of number of bites; DMI = dry matter intake; DMBM = dry matter bite mass; DMIR = dry matter intake rate

Several techniques have been developed over the years for estimating bite mass, bite rate and daily intake. Microphone-based methods are the most used devices for this purpose because they showed a good accuracy for jaw movements detection and allow three types of jaw movements to be differentiated: chew, bite and chew-bite, that are fundamental components of intake process (Ungar *et al.*, 2006b). Good results were achieved by combining video and acoustic recordings of ingestive behaviour in short-term studies. Laca & WallisDeVries (2000) for example, were able to correctly classify chews and bites (accuracy of 94%) and to predict intake with a good accuracy (R^2 = 0.90) by a linear combination of energy flux density in the chewing sounds and average intensity of biting sounds. Clapham *et al.* (2011) used an acoustic monitoring system to detect and analyse bites, and were able to differentiate bite and chew using a discriminant function with an accuracy of 94%. Galli *et al.* (2011) demonstrated that it is possible to accurately estimate DMI in grazing sheep by acoustic analysis (coefficient of variation = 18%, R^2 = 0.92), using chewing energy per bite and total amount of energy in chewing sound as the most important predictors, being able to integrate information about eating time and intake rate. Only few references can indeed be found on the use of acceleration sensors for the identification and classification of jaw movements. Umemura *et al.* (2009) succeeded to count cattle jaw movements with an accuracy of 90% compared with manual counts over 10 minute segments, modifying a pedometer into a pendulum.

Tani *et al.* (2013) used a 1-axis accelerometer coupled to a microphone, being able to distinguish cattle chewing activities at 90%, reaching 99% when the sensor was attached to the cow's horn. Umemura (2013) used three types of pedometers installed on neck collars to determine the accuracy with which the devices measured the number of grazing bites performed by cows. He found that the values recorded by the devices were linearly related to the number of bites recorded by visual observation, but concluded that this technique requires calibration to relate the pedometer values to the number of grazing bites. Andriamandroso *et al.* (2015) used a smartphone inertial measurement unit (IMU) which combined accelerometers, gyroscope, magnetometer and location sensors, to count the number of bites through frequency pattern of 1-axis acceleration data, achieving a mean error of 4–5% when compared with visual observations. Oudshoorn *et al.* (2013) used a 3-axis accelerometer to record cow bites at pasture, testing a series of thresholds values to determine the peak with the best correlation to the observation, but obtained an average correlation coefficient of only 0.65, similar to that obtained in our previous experiment (Giovanetti *et al.*, 2017) with sheep in grazing conditions. These results confirmed the difficulty to count bites using an accelerometer in free ranging animals, as more recently described by Rombach *et al.* (2018), that tried to validate the RumiWatch System (RWS; Itin and Hoch GmbH, Liestal, Switzerland) for the measure of ingestive and rumination behaviours of dairy cows during grazing and supplementation in the barn. The algorithms tested in the evaluation software were not able to differentiate between mastication and true bites while eating, indeed the number of bites is overestimated both for grazing and supplemented cows. They achieved a low relative prediction error *(≤ 0.10%)* for the number of rumination boluses, rumination chews, and total eating chews, but a higher error *(> 0.10%)* for the number of bites and time spent in biting and eating.

As the estimate of free-grazing animals intake is arduous, because of the difficulty of accurately establishing the weight of each bite, in the present study we have chosen to use sown micro-sward boards (Black & Kenney 1984) and to determine the average BM by weighing the micro-swards before and after the animal is fed. In complex grazing environments the best method available to estimate bite mass remains hand-plucking, that simulates a bite by mimicking grass prehension by hand and the estimations accuracy can be as high as 95% for cows and goats with trained operators (Bonnet *et al.*, 2011).

In the present study, the PLSR was able to provide better accurate estimates of the number of prehension bites, expressed as logarithm (LB), and DMI than DMBM, confirming how difficult it is to predict this variable with automated methods. This is a good result considering that bite is the elementary unit of the grazing process, therefore, by counting bites it is possible to determine their frequency, which, combined with the bite mass and the grazing time, allows calculation of herbage intake (Hodgson, 1985). Bonnet *et al.* (2015) recently studied the possibility of estimating bite mass combining the hand-plucking method with acoustic sensors coupled to the continuous bite monitoring, achieving an accuracy ranging between 80–94%. These results suggest that the combination of information provided by different sensors, such as microphones, accelerometers and GPS, can allow better estimates of intake at pasture. Moreover, the lack of differentiation between bite and chew can lead to overestimations of bites or to different accelerations signals from those originated by bites alone whereby, in agreement with other researchers (Laca & WallisDeVries, 2000; Giovanetti *et al.*, 2017; Rombach *et al.*, 2018) we believe that the differentiation between mastication chews and bites is very important for estimating intake and should therefore be integrated into validation models.

Conclusions

Accelerometer sensors placed under the jaw appear promising estimators of the number of bites as well as of DMI and DMIR variables even if at lower level. This is confirmed also by RMSEP that was very low when the number of bites were predicted, while it grew up for the other variables. Overall caution is advised when using accelerometer sensor to estimate intake in grazing conditions. A combination of information provided by different sensors and the integration of chews and chew-bites differentiation in validation models can allow probably better estimates. This approach warrants further research.

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References

Andriamandroso, A., F. Lebeau, and J. Bindelle. (2015). Changes in biting characteristics recorded using the inertial measurement unit of a smartphone reflect differences in sward attributes. In M. Guarino and D. Berckmans (eds). *Precision Livestock Farming* Proc. of 7th European Conference on Precision Livestock Farming, Milano, Italy. Pp. 283–289.

Andriamandroso, A.L.H., J. Bindelle, B. Mercatoris, and F. Lebeau. (2016). A review on the use of sensors to monitor cattle jaw movements and behaviour when grazing. *Biotechnol. Agron. Soc. Environ.*, 20.

Black, J.L. and P.A. Kenney. (1984). Factors affecting diet selection by sheep. II Height and density of pastures. *Austr. J. Agric. Res.*, 35: 565–578.

Blomberg, K. (2011). Automatic registration of dairy cows grazing behaviour on pasture. PhD Thesis. Swedish University of Agricultural Sciences, Uppsala, Sweden.

Bonnet, O., N. Hagenah, L. Hebbelmann, M. Meuret, and A.M. Shrader. (2011). Is hand plucking an accurate method of estimating bite mass and instantaneous intake of grazing herbivores? *Rangeland Ecol. Manag.*, 64: 366–374.

Bonnet, O.J., M. Meuret, M.R. Tischler, I.M. Cezimbra, J.C. Azambuja, and P.C. Carvalho. (2015). Continuous bite monitoring: a method to assess the foraging dynamics of herbivores in natural grazing conditions. *Anim. Prod. Sci.,* 55: 339–349.

Clapham, W.M., J.M. Fedders, K. Beeman, and J.P. Neel. (2011). Acoustic monitoring system to quantify ingestive behaviour of free-grazing cattle. *Comput. Electron. Agric.*, 76: 96–104.

Dimauro, C., R. Steri, M.A. Pintus, G. Gaspa, and N.P.P. Macciotta. (2011). Use of partial least squares regression to predict single nucleotide polymorphism marker genotypes when some animals are genotyped with a low-density panel. *Animal,* 5: 833–837.

Galli, J.R., C.A. Cangiano, D.H. Milone, and E.A. Laca. (2011). Acoustic monitoring of short-term ingestive behaviour and intake in grazing sheep. *Livest. Sci.*, 140: 32–41.

Giovanetti, V., M. Decandia, G. Molle, M. Acciaro, M. Mameli, A. Cabiddu, R. Cossu, M.G. Serra, C. Manca, and S.P.G. Rassu. (2017). Automatic classification system for grazing, ruminating and resting behaviour of dairy sheep using a tri-axial accelerometer. *Livest. Sci.,* 196: 42–48.

Hodgson, J. (1985). The control of herbage intake in the grazing ruminant. Proc. of the Nutrition Society, 44: 339–346.

Laca, E.A., & M.F. WallisDeVries. (2000). Acoustic measurement of intake and grazing behaviour of cattle. *Grass Forage Sci.*, 55: 97–104.

Milone, D.H., J.R. Galli, C.A. Cangiano, H.L. Rufiner, and E.A. Laca. (2012). Automatic recognition of ingestive sounds of cattle based on hidden Markov models. *Comput. Electron. Agric.*, 87: 51–55.

Orr, R.J., K.L. Young, J.E. Cook, and R.A. Champion. (2005). Development of a micro-sward technique for determining intake characteristics of perennial ryegrass varieties. *Euphytica,* 141: 65–73.

Oudshoorn, F.W., C. Cornou, A.L.F. Hellwing, H.H. Hansen, L. Munksgaard, P. Lund, and T. Kristensen. (2013). Estimation of grass intake on pasture for dairy cows using tightly and loosely mounted di-and tri-axial accelerometers combined with bite count. *Comput. Electron. Agric.*, 99: 227–235.

Rombach, M., A. Münger, J. Niederhauser, K.-H. Südekum, and F. Schori. (2018). Evaluation and validation of an automatic jaw movement recorder (RumiWatch) for ingestive and rumination behaviours of dairy cows during grazing and supplementation. *Journal of Dairy Science,* 101: 2463–2475.

Swain, D.L., and M.A. Friend. (2013). Opportunities for telemetry techniques in studies on the nutritional ecology of free-ranging domesticated ruminants. *Animal,* 7: 123–131.

Tani, Y., Y. Yokota, M. Yayota, and S. Ohtani. (2013). Automatic recognition and classification of cattle chewing activity by an acoustic monitoring method with a single-axis acceleration sensor. *Comput. Electron. Agric.,* 92: 54–65.

Tedeschi, L.O. (2006). Assessment of the adequacy of mathematical models. *Agric. Sys.,* 89: 225–247.

Umemura, K., T. Wanaka, and T. Ueno. (2009). Estimation of feed intake while grazing using a wireless system requiring no halter. *Journal of Dairy Science,* 92: 996–1000.

Umemura, K. (2013). Monitoring grazing bites and walking activity with pedometers. *Journal of Dairy Science,* 96: 1090–1093.

Ungar, E.D., N. Ravid, T. Zada, E. Ben-Moshe, R. Yonatan, H. Baram, and A. Genizi. (2006a). The implications of compound chew–bite jaw movements for bite rate in grazing cattle. *Appl. Anim. Behav. Sci.,* 98: 183–195.

Ungar, E.D., and S.M. Rutter. (2006b). Classifying cattle jaw movements: comparing IGER behaviour recorder and acoustic techniques. *Appl. Anim. Behav. Sci.,* 98: 11–27.

Watanabe, N., S. Sakanoue, K. Kawamura, and T. Kozakai. (2008). Development of an automatic classification system for eating, ruminating and resting behaviour of cattle using an accelerometer. *Jpn. Grassl. Sci.,* 54: 231–237.

Machine learning model for maternal quality in sheep

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Abstract

This paper aims to identify determinant traits of ewes by measuring their impact on lamb survival. For that, we devised a machine learning model that correlates ewe traits to lamb survival, and figured out as to which ewe traits explain the correlation and hence help us to identify the better mother.

In this study, we kept pregnant ewes under 24 h observation by two researchers starting approximately three days before expected parturition dates. We conducted the study using native and crossbreed lambs produced in high altitude and cold climate region. It is critical to note that parturation took place with minimum interruption unless there is a birth difficulty.

Independent variables used in the machine learning model pertain to mother's behaviours during parturation, however, we also took into consideration factors like dam breed, dam body weight at lambing, age of dam, litter size at birth, lamb breed and sex. Lamb survival is a nominal output variable, hence we tried out several classification algorithms like Bayesian Methods, Artificial Neural Networks, Support Vector Machine and Tree Based Algorithms. Classification algorithms applied for lamb survival were Bayesian Methods, Artificial Neural Networks, Support Vector Machine and Trees.

RandomForest algorithm was found best performer among tree algorithms.

We were able to present tree visualisation for mothering ability with 80% accuracy rate and 0.43 Kappa Statistics.

The result of the study shows that grooming behaviour is the first determinant mothering ability. If the grooming duration is longer than 15 minutes, then it is a good mother.

Keywords: maternal quality, lamb survival, machine learning

Introduction

Maternal effects play a significant role in offspring, however, in sexually reproducing animals, both parents are equally likely to affect the phenotype of offspring (Gowane *et al.,* 2014). It was emphasised that offspring's phenotype can be affected by parental phenotype with regard to significant impact on growth, survival and adaptation due to the fact that mothers transfer environmental information to their offspring (Mastropieri and Mateo, 2009). Neonate survival is dependent on the coordinated expression of appropriate behaviours from both mother and lamb (Dwyer, 2003) and behavioural interactions are much more important for prolific sheep with higher litter size.

Several studies have been conducted using machine learning algorithms to genomic prediction (e.g. review Gonzalez-Recio *et al.,* 2014). Machine Learning models help us to form prediction models that assist decision making. As we have large amount of data describing ewe traits using the data, we aim to set up a machine learning model so that the system continuously learns to figure out factors affecting lamb survival.

In this study, machine learning algorithms were studied in the behavioural and productive

traits affecting lamb survival of native and crossbreed lambs produced in high altitude and cold climate region.

Material and methods

In many areas of animal behaviour research, improvements in our ability to collect large and detailed data sets are outstripping our ability to analyse them.

These diverse and complex data sets exhibit nonlinear dependencies and unknown interactions across multiple variables. They may fail to conform to the assumptions of many classical statistical methods. The field of machine learning provides methodologies that are ideally suited to the task of extracting knowledge from these data.

We used classification trees as the method in this study. The classification trees are modern analytic techniques which are data-mining group tools [1, 2, 3, 6]. They allow for building graphic easily-comprehensible models used to describe and to predict the phenomenon expressed in both the nominal and the ordinal scale.

The classification trees can also be used for the purpose of preliminary selection of the traits which have a statistical effect on the dependent variable.

The structure of the classification tree starts with the entire information set (root node) (Figure 1). The subsets which emerge as a result of division are referred to as child nodes. The final subsets which are not exposed to further divisions are called leaves. The number of leaves determines the tree size, while the number of edges between the tree top and the most distant leaves informs about the tree depth. The classification trees have already been applied in financial management [2], medicine [1] as well in animal farming [15]. As per animal farming, Sawa *et al.* [15] used the classification tree technique to determine the genetic-and-physiological-and environmental parameters which ensure obtaining milk rich in protein and poor in somatic cells.

Experimental data

Individual and cohort data were combined into an original dataset. Our original dataset contains 1,351 event records from 193 individual lambs and 750 event records from 150 individual ewes from three different genotypes such as Awassi, Morkaraman and Tuj sheep breeds.

This data set contained 15 unique variables and several combinations, derived and redundant variables.

Lambs were born in April-May (spring) and under shed lambing conditions. Ewes were kept under 24 h observation by at least two researchers starting approximately three days before expected parturition dates. As it is described by Dwyer (2003), parturation took place with minimum interruption unless there is a birth difficulty. Sources of data on dam behavioural factors were used as stated by Emsen *et al.* (2012). Lambs were weaned at 60 days of age.

Independent variables used in the model are grooming, dam breed, dam age, dam weight at lambing, litter size at birth, lamb genotype, lamb breed, lamb sex, lamb birth weight. Output variable is mothering ability.

We scored mothering ability in this study according to the following observations: maternal vocalisation (low-pitched bleating), cooperation with lamb, attempts to find the udder and suckle, and absence of rejection or avoidance of the lamb. These are a series of dam behaviours that are used to measure mothering ability, as described by Dwyer (2014). Also, maternal behaviour decribed by Goursaud and Nowak (1999) shows that mother's intense grooming of the lamb is accompanied by several factors such as low pitch bleating and standing to suckle within the first six hours. These parameters facilitates sucking,

helps recognition of the lamb and formation of the ewe-lamb bond.

As indicated by Cloete and Scholtz, (1998) there are behavioural differences between breeds and some of the maternal behaviours which play a part in lamb survival are likely to be under genetic control.

According to our study, good mothering ability is described as follows: Ewe gets up within three minutes of lamb expulsion, vigorously grooms lamb and stands and facilitates suckling. Moderate mothering ability is described as follows: Ewe approaches lamb but does not initiate physical contact, circles when lamb attempts to suckle.

Poor mothering ability is described as follows: Ewe kicks/butts lamb and will not allow lamb to suckle.

In measuring maternal quality, we used WEKA (Waikato Environment for Knowledge Analysis) as the tool and Bayesian Methods, Artificial Neural Networks, Support Vector Machine and Trees as Classification algorithms.

Results and Discussion

Randomforest performed very well in classification of the mothering ability. Although RandomForest was found best performer among WEKA trees, visualize tree is not available. Therefore, we presented REPtree visualize tree for mothering ability with 75% accuracy rate and 0.27 Kappa Statistics in Table 1.

Table 1. Classification algorithms and accuracy rates for mothering ability

Algorithms	Correctly Classified Instances (%)	Kappa statistic	Mean absolute error	Root mean squared error	Relative absolute error	Root relative squared error
BayesNet	74.61	0.36	0.21	0.35	78.77	96.31
NaiveBayes	75.75	0.39	0.19	0.34	73.28	92.45
Multilayer Perceptron	72.72	0.25	0.20	0.40	75.67	109.43
SMO	75.75	0.19	0.29	0.38	109.23	103.68
RandomForest	83.33	0.54	0.17	0.30	65.66	82.30
Reptree	75.13	0.27	0.21	0.34	79.46	94.97

It can be observed clearly from visualize tree (Figure 1) that grooming behaviour is the first determinant for mothering ability. Grooming behaviour alone is almost sufficient to describe mothering ability if the grooming duration is longer than 15 minutes.

If grooming is more than 15 minutes, mothering ability is superior.

If grooming is less than 15 minutes, dam breed played an important role to describe mothering ability. While Awassi breed with less than 15 minutes grooming was still classified as good mother, Morkaraman breed with less than 15 minutes grooming were not classified as good mothers.

Tuj breed is known for its aggressiveness. Results showed that Tuj breed's mothering ability was related to their lamb birth weight. Lambs with lower birth weight (< 2.85 kg) were taken good care of by Tuj ewes.

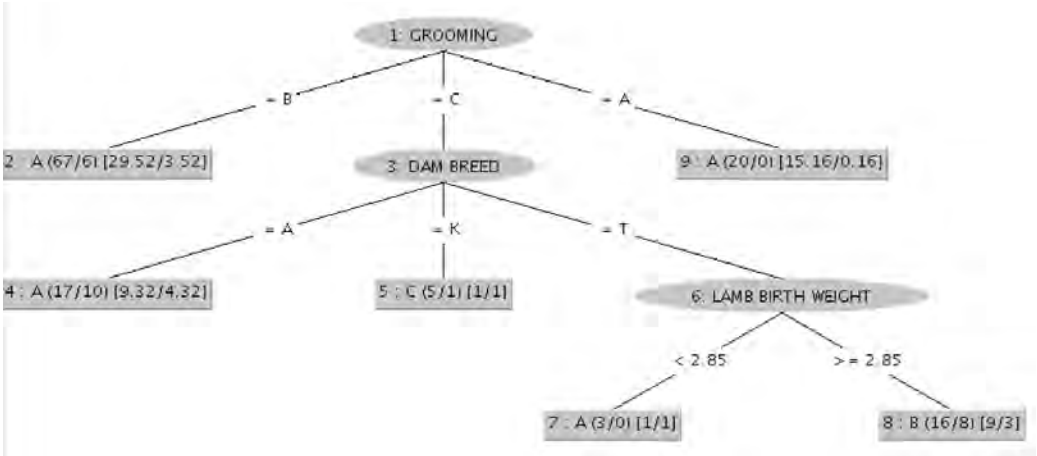

Figure 1. Mothering ability REPtree classification tree

Labels on outgoing edges from grooming refers to:

A: > 30 minutes grooming

B: 15-30 minutes grooming

C: < 15 minutes grooming

Leaf nodes depict mothering ability:

A: Good mothering (Ewe gets up within three min of lamb expulsion, vigorously grooms lamb and stands and facilitates suckling)

B: Moderate mothering (Ewe approaches lamb but does not initiate physical contact, circles when lamb attempts to suckle)

C: Poor mothering (Ewe kicks/butts lamb and will not allow lamb to suckle)

Lamb vigour is associated with ewe's behaviours towards the lamb, which is called mothering ability. We tested factors influencing mothering ability and found that grooming of the lamb is the main determinant of mothering ability. REPtree classification algorithm explains this relationship clearly in a tree visualization as depicted in Figure 1.

Conclusions

This study revealed that duration of grooming is a strong indicator of mothering ability. Ideal mothering ability requires at least 15 minutes of time spent for grooming. Another conlusion we found is that dam breed played an important role if grooming behaviour is weak. Awassi ewes' mothering ability was found unrelated to duration of grooming.

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References

Cloete, S.W.P., and Scholtz, A.J. (1998). Lamb survival in relation to lambing and neonatal behaviour in medium wool Merinos lines divergently selected for multiple rearing ability. *Australian Journal of Experimental Agriculture,* 38: 801–811.

Dwyer, C.M. (2003). Behavioural development in the neonatal lamb: Effect of maternal and birth-related factors. *Theriogenology,* 59: 1027–1050.

Dwyer, C.M. (2014). Maternal behaviour and lamb survival: from neuroendocrinology to practical application. *Animal,* 8: 102–112.

Emsen, E., Diaz, C.A.G., Yaprak, M., Koycegiz, F., Kutluca, M., Emsen, H. (2012). Effect of inter-breed embryo transfer on lamb growing performance and survival *Reprod. Dom. Anim.,* 47: 8–11.

González-Recio, O., Rosa, G.J.M., and Gianola, D. (2014). Machine learning methods and predictive ability metrics for genome-wide prediction of complex traits. *Livest. Sci.,* 166: 217–231.

Goursaud, A.P., and Nowak, R. (1999). Colostrum mediates the development of mother preference by newborn lambs. *Physiology & Behaviour,* 67(1): 49–56.

Gowane, G., Chopra, A., Prakash, V., Prince, L. (2014). The role of maternal effects in sheep breeding: A review. *Indian Journal of Small Ruminants,* 20: 1–11.

Mastropieri, D., and Mateo, J. (2009). Maternal effects in mammals. Chicago, IL: University of Chicago Press.

Mobile precision flock management tool for intensively managed meat sheep

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Abstract

A Mobile Sheep Manager Software (M-SMS) was developed for commercial lamb production model using cloud architecture that collects and utilises farm data and responds to the farm management with respect to insights on the operational and financial aspects of the farm. Metadata used in the software is composed of ewe reproductive performance, overall productivity, lamb growing rate, survival rate of newborns, and health status of flock. The system detects alerts occurring in the farm and suggests for troubleshooting. M-SMS was combined with Cloud Services compounded with Predictive Analytics Services for helping fine-tune flock management and improve operational excellence. Mobile Sheep Manager Software is aimed at sheep farmers who need an easy to use "point and click" solution to keep legislative records, to attain operational guidance and build flock performance data. The product supports for purchase, cull or breed decisions are based on targets of flock performance.

Keywords: software, sheep, precision flock management, predictive services

Introduction

Animal husbandry is one of the oldest agricultural practices in the world, but has benefitted little from monitoring and processing techniques currently being adopted by other industries. Contrary to mechanised industrial developments in livestock husbandry, research and development of appropriate technology for use in monitoring animals has fallen behind other technological improvements.

Mixing within an animal system refers to conditions where different types of animals are kept together. However, over the last three decades, small scale mixed livestock enterprise has been changed into large, single species units. Intensive and modern farming of single livestock make the farmer totally responsible for all livestock under his control. In such a system, animals now are produced intensively, and maintained under near ideal conditions for growth and production within current technological limits (Frost *et al.,* 1997).

Meat consumption is projected to rise nearly 73% by 2050 (FAO, 2011), and meat producing animals are required to be raised more efficiently for production and less impact for the environment. Moreover, the public is more concerned than ever about animal welfare, including both its monitoring and management (Butterworth, 2018). Precision livestock farming (PLF), can be defined as the management of livestock production using the principles and technology of process engineering (Wathes *et al.,* 2008). Europe has been the birthplace of PLF research, and it continues strongly with over three decades of research and innovation through at least four major EU-funded (EU-PLF, BioBusiness, AllSmartPigs, BrightAnimal) and many other national projects (Mottram, 2016; Wathes *et al.,* 2008). In livestock production, there are already a few examples of commercialisation of PLF techniques, but all of them focused on dairy cattle, poultry and pigs (Guarino *et al.*, 2008) and limited number of studies has been done in sheep breeding.

The purpose of this study is to report a Mobile Sheep Manager Software (M-SMS) tool developed for intensive sheep breeding for meat production for improving the efficiency

of production, while increasing animal and human welfare, via applying advanced information and management system (IMS) and Cloud and Predictive Machine Learning services.

Material and methods

Experimental data

Metadata used in this study is composed of the following: ewe reproductive performance, overall productivity, lamb growing rate, survival rate of newborns, feed cost, health status of flock and financial implications. We tested Mobile Sheep Manager Software (M-SMS) tool in intensively managed sheep flock (300 heads) at Er-Gen Biotechnologies Ltd R&D farm placed in Istanbul, Turkey for two consecutive years. Er-Gen has been raising sheep for meat production and breeding stock of maternal ewes since 2008 using a traditional recording and managing system. Flock was managed with M-SMS integrated data collection station. In order to determine the effectiveness of these tools, productive and management results of this farm were compared with the results of this particular farm before its implementation.

Data collection of individual and flock production information

Sheep in different categories such as breeding ewes, ewe-ram lambs, rams, weaned lambs, suckling lambs are RFID tagged and were tracked at their own production stages for creating inventories and setting targets for increase the lambs marketed per ewe.

Er-Gen practices a terminal crossbreeding program which requires maternal ewes with acceptable maternal characteristics.

Ewe flock was scored with the reproductive performance i) age at first lambing < 1,5 ii) lambing interval < 9 iii) litter size at weaning > %180 iv) total productivity (total kg of lambs at weaning) > 30kg. Being able to analyse lambing percentage, the number of open ewes and weaning reports helped to focus on ways to improve ewe productivity. Terminal crossbred lambs were scored for i) birth weight ii) weaning weight iii) average daily gain weight (ADW) iv) feed conversion rate v) dressing percentage. Rams were subjected to individual tests for their reproductive performance i) scrotum circumference ii) body weight iii) libido test.

M-SMS creates reports to analyse ewe performance, identifying both the top and the bottom producing ewes in the flock. Time-tune culling decision for ewes was automatically generated by M-SMS and notified the breeder through his smartphone. By doing so, unproductive ewes are culled on time to avoid their negative impacts on profit margins and selecting replacement ewe lambs from the right ewes improved overall flock productivity. The system autonomously improves decisions made on culling through machine learning algorithms that are trained by farm data on a weekly basis.

Data Collection Station

Data Collection Station is a three meter long, 3-way sorting drafting gateway that is equipped with sensors to collect weight data, and RFID tag of the animal as well as the operation performed on the animal inside the unit. The unit is equipped with 3-way drafting, ultrasound scanning unit, weight platform and RFID reader to get an individual recording of the animal for different purposes of productivity measurements. Single station for multiple purposes was used to precisely collect animal data.

Cloud Computing

Cloud Computing is a natural fit to enable precision flock management on a farm, in a way that it utilises sensors attached to an auto drafting unit, and electronic tags attached to

the animals to facilitate data collection. All these devices are IoT devices connected to a cloud system, and they push data when a critical event occurs on the farm. It is the cloud infrastructure that collects, measures, analyses and suggests improvements.

Mobile Flock Management Software

The Mobile Sheep Manager Software (M-SMS) is aimed at sheep farmers who need an easy to use "point and click" solution to keep legislative records and build flock performance data. The product is an invaluable support for purchase, cull or breed decisions based on targets of flock performance. It provides suggestions with no bias, purely based on farm data.

Results and discussion

The Mobile Sheep Manager Software and other integrated tools for precision flock management increased significant efficiency of an intensively managed sheep farm for lamb production. Users performed very well in adapting to tools when animals are needed to be sorted, weighed, treated and scanned.

Precision management of pregnant ewes reduced neonatal lamb mortality from 13% to 5%. Pregnancy rate in ewe lambs increased from 70% to 94% thanks to steady growth which was assured by M-SMS. Thomas (2002) suggested that level of nutrition should be targeted towards maintaining a gain of at least 0.4 lbs/day before and throughout breeding. Another achievement for reproductive success was the 20% increase in the mature ewes in accelerated eight-monthly lambing schedule. Total productivity of ewes was recorded as average 44 kg which is 14 kg more than previous years. Barren ewes' ratio was significantly reduced from 10% to 3%.

Efficient use of feed energy has an important link for both in animal welfare and environmental impact. Norton and Berckmans (2018) emphasised the fact that we need more animal product with less feed, less manure and emissions. In our current study, feed cost was found to be one of the strategically important improvements with 23% decrease recorded for total feedstuffs used per ewe.

There is no doubt that Precision Flock Management is potentially one of the most powerful technology to revolutionise the intensive sheep farming industry. The significant result of this study is that if properly implemented M-SMS could definitely improve farm profitability increase in animal welfare and reduce labour and feed costs. PFM developed and tested in the case study farm within EU Project (iSAGE), quickly took interest of other intensive sheep farmers which shows successful commercialisation potential of this technology. As stated by researchers (Thysen, 2000 and Lewis, 1998) for the other livestock industries and agribusiness, we found that efficient information management is very much a part of profitable intensive sheep production. Farmers and/or investors choosing intensive sheep farming showed great interest and were found to be quite convincing when using M-SMS applications which supports the operational aspects of sheep farming in intensive management system.

The challenge to the sheep breeding M-SMS development is to organise the flow of data and the proper interpretation of data. When sheep are raised under an intensive system, organising the data collection and interpretation of the data is less complex compared to semi-intensive and extensive system in which environmental and external factors are much more complex.

Conclusions

It is concluded that through the adoption of M-SMS for precision sheep breeding has the potential to improve production efficiency and reduce costs. To ensure that the potential

of M-SMS is developed for intensive sheep breeding, we need to verify it in the same flock for a lifetime cycle; also in different genotypes used for maternal line and different market needs for commercial lambs in terms of slaughter weights and ages.

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References

Butterworth, A. (Ed.). (2018). Animal welfare in a changing world.CABI.

FAO. (2011). World livestock (2011). In A. McLeod (Ed.), Livestock in food security (p. 115). FAO. ISBN: 978-92-5-107013–0.

Frost, A.R., Schofield, C.P., Beaulah, S.A., Mottram, T.T., Lines, J.A. and Wathes, C.M. (1997). A review of livestock monitoring and the need for integrated systems. *Computers and Electronics in Agriculture,* 17: 139–159.

Guarino, M., Guarino, M., Jans, P., Costa, A., Aerts, J.M., Berckmans, D. (2008). Field test of algorithm for automatic cough detection in pig houses. *Computers and Electronics in Agriculture*, 62(1): 22–28.

Lewis, T. (1998). Evolution of farm management information systems. *Computers and Electronics in Agriculture*, 19(3): 233–248.

Mottram, T. (2016). Animal board invited review: Precision livestock farming for dairy cows with a focus on oestrus detection. *Animal,* 10(10): 1575–1584.

Thomas, D.L. (2002). Breeding ewe lambs or getting the most out of ewe lambs. www.ansci.wisc.edu/extension-new%20copy/sheep/etn_01/feb/ewelambs.doc.

Thysen, I. (2000). Agriculture in the information society. *Journal of Agricultural Engineering Research*, 76(3): 297–303.

Pilot study to assess the accuracy of the RumiWatch noseband sensor for detecting grazing behaviour of sheep

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Abstract

The quantification of grazing behaviour of free-ranging animals such as sheep can help to improve the efficiency of animal production on rangelands. The understanding of the interaction between animals and sward characteristics can be investigated based on detailed knowledge of the grazing process of animals. However, there are few sensors available to measure grazing behaviour of sheep for long-term periods. The RumiWatch noseband sensor is an automated measurement system, which is already validated and established for recording feeding behaviour of cows and horses. The objective of this study was (1) to validate two versions of prototypes of the RumiWatch noseband sensor, which were adapted to sheep and (2) to analyse the agreement, when raw data were converted with two different analysis software versions. Visually observed behavioural data for 16 Merino sheep were compared against data automatically gathered by the sensors. These sensor systems are able to record data of detailed grazing behaviour (such as grazing and rumination time). The results demonstrated that there is a high correlation detected for measuring grazing behaviour of sheep with the analysis software of cattle. There is an influence on the accuracy of the sensor based on the analysis software version as well as the prototype, the results are ranging between a Pearson's r of 0.90 and 0.95 for grazing time and r = 0.70 and r = 0.88 for rumination time, respectively. These results showed that there is potential to use the RumiWatch system for measuring grazing behaviour of sheep.

Keywords: grazing management, feed intake, ewes, rumination, pasture

Introduction

Optimised grazing management systems seek to control the relationship among animals, plants and soil by regulating the number of animals and the duration and location of animals. This does include a greater understanding of diet selection and activity of livestock within grazing systems (Cox *et al.,* 2017). Grazing behaviour as well as pasture intake (and the efficiency of its use for liveweight gain) for various livestock species has always been difficult to measure long-term under field conditions (Cottle, 2013). In comparison to housed animals with feed provided, the quantification of the feed intake on pasture is difficult to obtain. On pasture, some approaches to quantify the intake are based on either plant biomass or animal parameters (Rombach *et al.,* 2019). However, some of the measurement methods can disturb normal grazing behaviour and interfere with the intake (Cottle, 2013). Therefore, a sensor technology, which can automatically gather data on grazing behaviour without inhibition of natural behaviour can be beneficial.

There are already various approaches to using sensor technology to measure grazing behaviour on cattle (e.g. Andriamandroso *et al.,* 2016), however, the application of the sensors on sheep is limited. The RumiWatch noseband sensor is a commercially available sensor technology, which is able to gather detailed grazing behaviour of dairy cows, such as grazing and rumination time as well as a classification of jaw movements into grazing bites and rumination chews (Werner *et al.,* 2018). This technology was therefore adapted to be tested in a pilot study on grazing sheep. For this, the noseband was reduced and the halter

was modified to fit on a sheep's head. The first aim of the study was to test two different prototypes of the noseband sensor for sheep. One sensor had the datalogger and battery placed on top of the head, whereas the other one had the technical components placed on the right side of the cheek. Without any further adaptations of the generic algorithms in the analysis software (RumiWatch Converter), the automated measurements of the noseband sensor were compared against the gold standard of visual observation. There are various different versions of the RumiWatch Converter available depending on the species, e.g. cattle or horses, and depending on the feed intake behaviour of the cattle, namely either grazing on pasture, or feeding in a housed system. Therefore, the second aim of this study was to compare different RumiWatch Converter versions against visual observation to assess the agreement.

Material and methods

The trial was conducted at the research station for sheep "Oberer Lindenhof" of the University of Hohenheim in Eningen, Germany over a period of four weeks from 14 August to the 07 September 2018. The experimental area was permanent grassland with ryegrass, meadow grass as well as clover and herbal contents. The average sward height was 4.3 ± 1.7 cm.

Experimental design

In total, there were 16 merino ewes selected, which were accompanied by their lambs. A group of four ewes per week was kept separately in a paddock for visual observation. The average body weight of the ewes was 73 ± 10.4 kg, with a mean number of lambs of 1.3 ± 0.4 and a mean lambing date of 27/07/2018 at the beginning of the experiment. During the experiment the group of focal sheep was kept on the paddocks from 08:00–16:00 h and was supplemented in the barn with hay. Prior to sending the sheep to the paddock, each morning two of the sheep were equipped with the noseband sensors, which were removed when the sheep returned to the barn. The first two days per week, two sheep out of the group were equipped with the same sensors, whereas for the last two days of a week the focal sheep alternated.

Behavioural data was obtained by visual observation with one observer as a gold standard to compare against the automated sensor measurement. There were four measurement days per week from Tuesday to Friday. Within each day, there were two, two hour periods of observation of two sheep equipped with sensors, where a one minute scan sampling protocol was conducted by the observer to classify each minute in either grazing, rumination or other activity. "Grazing" was defined as the behaviour for feed intake e.g. ripping the grass or mastication of ingested grass, whereas "Rumination" was defined as the regurgitation, chewing, salivation and swallowing of ingested grass. If the sheep did not show any of the mentioned behaviours, the minute was classified as "Other Activities". The data were recorded on a spreadsheet and were transferred manually to an electronic spreadsheet (Microsoft Excel Version 2010; Microsoft Corporation, Redmond, USA) for analysis. The observation times per day changed every week and were either 08:00 - 10:00 hrs and 11:00 - 13:00 hrs or 11:00 - 13:00 hrs and 14:00 - 16:00 hrs to capture the behaviour of the sheep over the full grazing period.

The automated sensor system consisted of two prototypes of the RumiWatch noseband sensor (Itin+Hoch GmbH, Liestal, Switzerland), which were adapted to fit on sheep. Further information about the technical specification of the noseband sensor can be found in a study by Werner *et al.,* 2018. On one of the prototypes (head), the datalogger, including the accelerometer and the battery supply was placed on top of the head, see also Figure 1, whereas on the second prototype (cheek), the box with the datalogger and battery was

placed on the level of the sheep's right cheek, see Figure 2. The RumiWatch Manager 2 (V.2.1.0.0) was used to synchronise both RumiWatch devices to UTC (Universal Time Coordinated) at the beginning of the experiment.

Figure 1. Sensor prototype 1 (head), the plastic box with datalogger and battery placed on the head of the sheep

Figure 2. Sensor prototype 2 (cheek), the plastic box with datalogger and battery placed on the right side of the sheep's head

Data preparation and analysis

This visually recorded data at one-minute intervals were totalled for one hour periods, which included data for the time durations of the specific behavioural classifications, which resulted in 100 hours (6,000 min) of valid observations in total.

The automatically captured raw data were converted by two versions of the assigned analysis software for the noseband sensor, namely the RumiWatch Converter (RWC). Both versions of the RWC were developed for cows. The first version V0.7.3.2 (V2) was developed and validated for housed cows by Zehner *et al.*, 2018. This RWC version does not include the accelerometer for distinguish the head position of a cow. The second version of the RWC V0.7.3.36 (V36) was developed as an advanced version of V2 for grazing cows, see Werner *et al.,* 2018. This version integrated the accelerometer to distinguish the head position of a cow in either head up or head down, to measure grazing bites and to further improve the classification of rumination of cows on pasture.

Statistical analysis was performed using R version 3.5.1 (R Foundation for Statistical Computing, Vienna, Austria). A number of tests were conducted to assess agreement between data of the noseband sensor and visual observations. A Pearson's correlation coefficient (r) and a concordance correlation coefficient (CCC) was calculated. Interpretation of r -values and CCC were based on criteria defined by Hinkle *et al.,* (2003) as follows: Negligible = 0.0 - 0.3, low = 0.3 - 0.5, moderate = 0.5 - 0.7, high = 0.7 - 0.9 and very high = 0.9 - 1.00. Furthermore, the Bland-Altman-analysis was conducted, which indicated the mean differences (bias) between the paired automatically recorded and visually observed values, as well as the lower and upper 95% limits of agreement (LoA). The limits of agreement were calculated as ± 1.96*standard deviation from mean difference.

Results and discussion

The results of the comparison between visual observation and automated measurement for measuring grazing time of sheep are presented in Table 1. The median measured by visual observation for grazing time was 28 min/h, while observing sheep wearing the head sensor and 30 min/h for the cheek sensor. The automated measurement of the head sensor was measuring as a median 33 min/h, when analysed by V2 and 30 min/h analysed by V36, respectively. The median value for measuring grazing time by the cheek sensor was 36 min/h for V2 and 30 min/h for V36.

The Bland-Altman analysis revealed that the grazing time was slightly overestimated by the head sensor in comparison to visual observation with a mean bias of 3.9 min/h, when using V2 and 0.1 min/h using V36, respectively. The higher correlation of V36 compared to visual observation was also demonstrated in a higher r-value with 0.93 and a CCC = 0.93, whereas V2 had a correlation of automated measurement and visual observation of r = 0.90 and a CCC = 0.88.

Contrary to the results of the head sensor, there was a higher correlation between the automated measurement and visual observation detected by V2 with an r-value of 0.95 and a CCC-value of 0.93 compared to r = 0.91 and CCC = 0.87 for V36, respectively. The mean bias for V2 demonstrated an overestimation of grazing time by the sensor with 3.2 min/h compared to visual observation, whereas V36 underestimated the grazing time by -3.7 min/h.

Table 1. Statistical analysis of grazing time with Pearson's r, concordance correlation coefficient (CCC) and Bland-Altman-analysis (mean bias, lower 95% limit of agreement (LoA) and upper 95% limit of agreement (LoA) while using different sensor positions and converter versions

Sensor position	Converter-version	Pearson's r	CCC	Mean bias	Lower LoA	Upper LoA
Head	V2	0.90	0.88	3.9	-10.4	18.25
	V36	0.93	0.93	0.1	-11.7	12.0
Cheek	V2	0.95	0.93	3.2	-7.3	13.6
	V36	0.91	0.87	-3.7	-17.5	10.2

In Table 2, there are the results of the statistical analysis for the comparison of visual observation to the automated measurement of rumination time presented. Visually observed median rumination time, while observing sheep with head sensor, was 3 min/h and median visual rumination time for the cheek sensor was 10 min/h. The noseband sensor "head" was measuring a median rumination time of 9 min/h for V36 and 3 min/h for V2, respectively. V36 analysed a median rumination time for the cheek sensor of 19 min/h and 11 min/h, when the RWC V2 was used.

In general, the agreement of visual observation and automated measurement was lower for rumination time in comparison to measuring grazing time. This is demonstrated in a lower Pearson's r for the head sensor with an r-value of 0.88 for both Converter versions and a CCC-value of 0.75 for V36 and 0.87 for V2, respectively. The correlation between visual observation and the automated measurement for the cheek sensor was also high with an r-value of 0.70 for V36 and r = 0.87 for V2. There is also a higher agreement demonstrated for analysing the raw data with V2 in comparison to V36 when comparing the CCC-values for the cheek sensor with a CCC = 0.52 for V36 and a CCC = 0.86 for V2.

For both sensor prototypes, the Bland-Altman analysis revealed that rumination time was

overestimated by both sensors regardless of the Converter versions. However, rumination time is measured more accurately by the Converter version V2 in comparison to V36, while using both prototypes. For the sensor cheek the mean bias for rumination time was lower for V2 with 1.3 min/h on average compared to V36 with a mean bias of 7.8 min/h in comparison to a mean bias of 1.1 min/h for V36 and 4.5 min/h for V2, when measured by the sensor head.

Table 2. Statistical analysis of rumination time with Pearson's r, concordance correlation coefficient (CCC) and Bland-Altman-analysis (mean bias, lower 95% limit of agreement (LoA) and upper 95% limit of agreement (LoA) while using different sensor positions and converter versions

Sensor position	Converter-version	Pearson's r	CCC	Mean bias	Lower LoA	Upper LoA
Head	V2	0.88	0.87	1.1	-6.8	9.1
	V36	0.88	0.75	4.5	-3.3	12.3
Cheek	V2	0.87	0.86	1.3	-8.7	11.3
	V36	0.70	0.52	7.8	-6.6	22.2

Overall the results demonstrated that both sensor prototypes are able to measure grazing time accurately with a high or even very high correlation in comparison to visual observation. However, depending on the Converter version, there was a better correlation detected for grazing time, when the raw data captured by the sensor head were analysed with V36 compared to V2. This might be due to the reason that the converter V36 is integrating the accelerometer measurements to detect grazing behaviour of cows. Although the positioning of the datalogger and accelerometer differed from the position of the technical components on a cow's head, there was still a higher correlation and a lower mean bias for the head sensor then the cheek sensor for measuring grazing time. The difference in the grazing behaviour of both species might influence positively the better detection of grazing by the head sensor than by the cheek sensor, as the sheep are not ripping the grass with their tongue, accompanied by a very special head movement as it can be seen by a cow. This specific movement is captured by the accelerometer of the sensor technology with Converter version V36 and can be integrated in a successful detection of grazing bites. This fact is also enhanced by the result of the cheek sensor, which had a higher correlation of visual and automated measurement for V2 than V36. Within the Converter V2, which was developed for housed cows, the algorithms do not include the accelerometer measurements to a larger intention for measuring feeding behaviour of cows. Therefore, this version is less sensitive to detect specific head movements. This might explain the better accuracy of measuring grazing time when using the Converter V2 and the prototype cheek.

Contrary to the measurement of grazing time, there was a higher correlation detected by the head sensor for measuring rumination time with the Converter version V2. As described before, this might be also due to the decreased sensitivity of V2 in comparison to V36. Therefore, the less advanced Converter version V2 showed more robust results, than the advanced Converter version V36.

The RumiWatch noseband sensor is also able to classify each jaw movement of cattle into either grazing or mastication bite, rumination chew or any other jaw movement, which is not assigned to any mentioned category. In further studies, this might be the next level to test the feasibility of the noseband sensor to also measure those parameters for sheep. However, the accurate recording of grazing time and rumination time is already

an improvement to laborious visual observation. The application of the automated measurement over long-term periods may now deliver a better understanding of grazing behaviour of sheep and is also beneficial for an improved grazing management.

Conclusion

The results of this pilot study on sheep demonstrated that it is possible to measure grazing and rumination time on a 1 h resolution accurately with the RumiWatch noseband sensor based on the cows' analysis software. Depending on the parameter, the converter version and the positioning of the datalogger and the accelerometer influenced the accuracy. This means that the highest correlation between visual observation and automated measurement was detected for grazing time while using the head sensor with the Converter version V36. In comparison to this, for rumination time, the highest correlation was detected for the head sensor with using Converter version V2. These results give a first indication for further development of the sensor technology to be used on sheep. For a high accurate sensor technology to measure grazing behaviour, a tailored hybrid version of the Converter versions to sheep`s behaviour may be beneficial. Combined with further data collection and improvements on the correct positioning of the technical components on a sheep's head, the application of the RumiWatch on sheep can be realised.

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References

Andriamandroso, A., J. Bindelle, B. Mercatoris, and F. Lebeau. (2016). A review on the use of sensors to monitor cattle jaw movements and behavior when grazing. *Biotechnology, Agronomy, Society and Environment,* 20(S1): 1–14.

Cottle, D.J. (2013). The trials and tribulations of estimating the pasture intake of grazing animals. *Animal Production Science,* 53(11): 1209–1220.

Cox, F., Badgery, W.B., Kemp, D.R., and Krebs, G. (2017). Seasonal diet selection by ewes grazing within contrasting grazing systems. *Animal Production Science*, 57(9): 1824–1836.

Hinkle, D.E., Wiersma, W., Jurs, S.G. (2003). Applied statistics for the behavioural sciences. 3rd edition. Houghton Mifflin, Boston, MA, USA.

Rombach, M., Südekum, K.H., Münger, A., and Schori, F. (2019). Herbage dry matter intake estimation of grazing dairy cows based on animal, behavioral, environmental, and feed variables. *Journal of Dairy Science, in press*.

Werner, J., Leso, L., Umstatter, C., Niederhauser, J., Kennedy, E., Geoghegan, A., Shalloo, L., Schick, M. and O'Brien, B. (2018). Evaluation of the RumiWatchSystem for measuring grazing behaviour of cows. *Journal of Neuroscience Methods*, 300: 138–146.

Zehner, N., Umstätter, C., Niederhauser, J.J., and Schick, M. (2017). System specification and validation of a noseband pressure sensor for measurement of ruminating and eating behavior in stable-fed cows. *Computers and Electronics in Agriculture*, 136: 31–41.

Development of a predictive model to identify the day of lambing in extensive sheep systems using autonomous Global Navigation Satellite System (GNSS)

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Abstract

The aim of this project was to develop a model capable of predicting day of lambing from GNSS data. A field trial was conducted in New Zealand over a two-week period from September to October 2017. Forty ewes were fitted with GNSS tracking collars, recording at three-minute intervals. Animals were visually observed to record birth events. Of the 40 ewes, 25 lambed during the experimental period. A heuristic model was developed to predict the day of lambing by classifying ewes as either 'non-lambing' or 'lambing' on each day of the study based on her speed of movement, mean distance to peers and extent of spatial landscape. Predictions were based on the series moving over or under a given threshold, determined through estimated least-square means from the linear mixed-effects statistical analysis. The overall accuracy of the model was 83.0%, with a sensitivity of 63.6% and specificity of 84.1%. The results of this project highlight the potential for GNSS tracking for post-hoc detection of lambing events. This could be used to inform graziers on the status of individual animals and their flock as a whole, particularly in extensive farming systems where close observation may be limited. Further work should be conducted on larger datasets to improve reliability of results.

Keywords: behaviour monitoring, GNSS, movement metrics, parturition, sheep, spatio-temporal

Introduction

Appropriate animal welfare is critical for all livestock production systems. Whilst historical focus has been on welfare standards for intensively-raised animals, issues associated with extensive production systems are still significant. In countries such as Australia where farm size can be taken to the extreme, large stock numbers and little manpower often make regular inspection of animals difficult (Petherick, 2006). In neighbouring New Zealand, whilst farms are not as physically large, many cover mountainous terrain (Kelly & Smith, 2012) which can also make animal inspection problematic. This raises concerns for complying with welfare standards.

Autonomous on-animal sensors offer a solution to this issue, improving capabilities for monitoring individual animals. This is particularly attractive during critical times of an animal's life, for example, parturition where the welfare and productivity of both the mother and offspring are challenged. Previous studies by Dobos *et al.* (2014) and Dobos *et al.* (2012) have examined behavioural changes in ewes using GNSS technology. In Dobos *et al.* (2014) mean daily speed decreased at lambing and mean distance to peers increased on the day of birth. In Dobos *et al.* (2012), pregnant Merino ewes significantly reduced their home range size on the day of lambing compared to the seven days prior. While the ability of Global Navigation Satellite System (GNSS) sensors to detect behaviour change is clear, the use of this data to develop predictive models is yet to be widely explored.

This study used GNSS tracking collars to monitor sheep behaviour at parturition. Metrics derived from sensor data were then used to develop a heuristic model that could indicate

if a ewe had given birth within a 24 h period. This represents the first attempt to develop a post-hoc predictive model for lambing detection at a day-scale.

Material and methods

Experimental data

The field trial was conducted at a mixed enterprise property in North Canterbury, New Zealand from September to October 2017. Forty pregnant ewes (20 twin-bearing and 20 single-bearing) were randomly selected from the larger commercial flock based on confirmed pregnancy and expected lambing day. Ewes were fitted with GNSS tracking collars recording at three-minute intervals. Ewes were also fitted with identification bibs to allow individual recognition from a distance. After collar and bib attachment, ewes were monitored for signs of distress before being moved to the experimental paddock (3.09 ha).

Ewes were observed from a neighbouring paddock using binoculars. Video observations were also conducted. Animals were observed *ab libitum* to record birth events for a total of 14 days. Collars and bibs were removed and downloaded at the conclusion of the trial.

GNSS data analysis

GNSS data was downloaded and processed using R (R Core Team, 2018). Speed of travel between consecutive GNSS locations was calculated and speeds > 3 m s^{-1} were excluded (Taylor *et al.*, 2011). A moving average for each location was then calculated using the two preceding and two following values. All data analysis was conducted using this dataset, with the exception of 95% minimum convex polygon (MCP) calculation where data was 'trimmed' to exclude any locations apparently outside of the paddock boundaries.

The data was then randomly split into a 50:50 training and test set, with individual animals allocated in their entirety. The following metrics were calculated: (i) daily speed of movement (mean, minimum, maximum); (ii) daily mean distance to peers; and (iii) daily paddock utilization by way of MCP. This was analyzed using a linear mixed-effects models with significance of $P < 0.05$. Least-square means (Lsmeans) were generated with Tukey adjustment.

Heuristic model development

A heuristic model was developed to predict the day of lambing by classifying ewes as either 'non-lambing' or 'lambing' on each day of the study based on her speed of movement (mean, maximum and minimum), mean distance to peers and extent of spatial landscape utilisation (95% MCP). Predictions were based on the series moving over or under a given threshold, determined through estimated Lsmeans from the linear mixed-effects statistical analysis.

Results and Discussion

Of the 40 ewes, 25 lambed during the experimental period. Three ewes were removed from analysis due to GNSS collar failure or incomplete datasets.

The estimated lsmean based on the training dataset is shown in Table 1. These were used as the threshold values in model development. If the calculated daily values for each animal were below (mean, maximum daily speed, 95% MCP) or above (minimum daily speed, mean distance to peers) the threshold, this was flagged as a potential 'lamb' day. The heuristic model developed dictated that animals had to be flagged for at least three of the five criteria to be classified as 'lambing'.

Table 1. Estimated least square (Lsmean) for day of lambing. Values include standard error (SE)

Metric	Lsmean ± SE
Mean daily speed (m s^{-1})	0.044 ± 0.002
Maximum daily speed (m s^{-1})	0.18 ± 0.03
Minimum daily speed (m s^{-1})	0.011 ± 0.0007
Mean distance to peers (m)	30.8 ± 0.08
95% MCP (%)	49.8 ± 2.55

The overall accuracy of the model was 83.0%, with a sensitivity of 63.6% and specificity of 84.1%. Of the 11 animals assessed, seven lambing days were correctly identified. These results are summarized in Table 2.

Table 2. Confusion matrix where values in bold are correct observations

Predicted	Observed behaviour	
	Lamb	Non-Lamb
Lamb	7	33
Non-lamb	4	174

As shown in Table 2, whilst the model correctly identified the majority of true lambing events, 33 non-lambing days were also classified as lambing (i.e. false positive). In a real-life situation, this number of false alarms would not be practical. Thus, there is a need for further development of a model that reduces the number of false alarms but ensures true events are not missed. Research should also be conducted using a larger number of animals and with an improved validation of the model with an independent data set or cross-validation procedure.

Given this model has been developed using specific threshold values, we would not expect this model to have universal application across all sheep systems. Instead, this model represents a first attempt to develop a heuristic model for lambing prediction in an effort to explore how GNSS data could be applied in a commercially available tracking system.

Conclusions

This study supports the use of GNSS tracking for post-hoc detection of lambing events. This information could be used in the development of online detection models that can detect if a ewe has given birth in the preceding 24 h. This information would be beneficial for graziers, allowing them to improve management of their animals, particularly in extensive farming systems where close observation may be limited. There is an obvious opportunity to move on from this basic heuristic modelling process to more advanced machine learning and time series analysis, and this will be explored in future work.

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References

Dobos, R.C., Taylor, D.B., Trotter, M.G., Hinch, G.N. (2012). Can home range be used as an identifier of lambing for grazing pregnant Merino ewes. In: *Proc. 29th Biennial Conference of the Australian Society of Animal Production* Christchurch, New Zealand, 47.

Dobos, R.C., Dickson, S., Bailey, D.W., Trotter, M.G. (2014). The use of GNSS technology to identify lambing behaviour in pregnant grazing Merino ewes. *Animal Production Science,* 54: 1722–1727.

Kelly. S., Smith, W. (2012). Marginality, adaptation and farming in the New Zealand high country. *Journal of Alpine Research,* 100(1).

Petherick, J.C. (2006). Animal welfare provision for land-based livestock industries in Australia. *Australian Veterinary Journal,* 84: 379–383.

R Core Team, (2018). R: A Language and Environment for Statistical Computing. https://www.R-project.org, Vienna, Austria.

Taylor, D.B., Schneider, D.A., Brown, W.Y., Price, I.R., Trotter, M.G., Lamb, D.W., Hinch, G.N. (2011). GPS observation of shelter utilisation by Merino ewes. *Animal Production Science,* 51: 724–737.

Precision livestock farming: National Institute of Food and Agriculture contributions and opportunities

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Abstract

The global population of 10 billion expected by 2050 will require an increase in food production of approximately 70%. Increasing productivity, sustainability, decreasing ecological footprint of agriculture, and improving health (animal, human, plant) are some challenges faced by agriculture today. Approaches such as precision livestock farming (PLF) are required to meet growing demands for animal products. Successful implementation of PLF requires a multidisciplinary approach from experts in academia, industry, government and nongovernmental sectors. Governments play an essential role by establishing policies, supporting precompetitive research, spurring innovation through translation of research by industry, and facilitating adoption of research findings by users such as farmers, ranchers, processors and consumers. The U.S. Department of Agriculture National Institute of Food and Agriculture (USDA-NIFA) is the USDA's primary extramural science agency that administers funding for programs to advance agriculture-related sciences. The goal of this study was to characterise the agency's past contributions in PLF research and education, and to define key challenge areas and opportunities. To date, U.S. investments in precision agriculture have focused on crops rather than animals. NIFA has invested 14 million USD in 50 competitively funded projects over the last decade. Of these, the major concepts include diseases, emissions and tool development. As USDA moves forward with a focus on new technologies to increase profitability in American agriculture, it anticipates that there will be opportunities for collaborations in PLF. The results of this study may help chart the future directions in supporting PLF research at the federal and global level.

Keywords: Federal research investments, international collaborations, National Institute of Food and Agriculture, precision livestock farming

Introduction

The global population of 10 billion expected by 2050 will require an increase in food production of approximately 70% (FAO, 2009). Animals supply 43% of total protein in human diets world-wide (FAO, 2010) and the demand for animal products will double by 2050 (Figure 1) (Alexandratos & Bruinsma, 2012; Chan *et al.*, 2017). To meet future demands, animal agriculture will need to boost production and do so while maintaining or reducing its requirements for land, water and feed. Moreover, adjustments to fluctuating production factors associated with climate change and consumer preference shifts must be made. Additionally, decreasing ecological footprints and improving health of animals, humans and plants are some grand challenges faced by agriculture today.

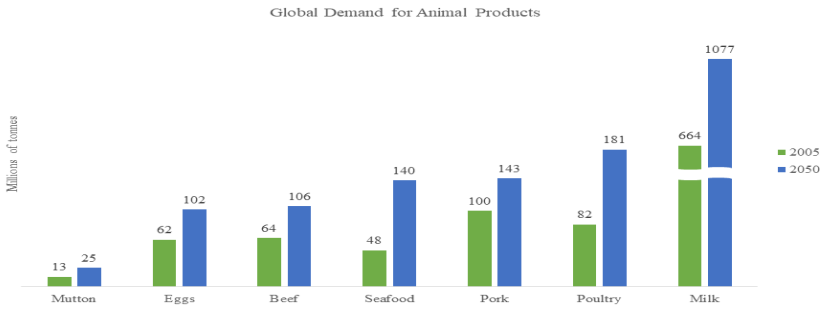

Figure 1. Global demand for animal products is expected to dramatically increase
Source: Alexandratos & Bruinsma, 2012; Chan *et al.*, 2017

Animal production approaches that better utilize technologic innovation, such as precision livestock farming (PLF), are required to meet growing demands for animal products. We encompass traditional livestock species along with poultry, bees, and aquaculture species when referring to PLF. Defined as the continuous real-time monitoring of individual animals for health, welfare, production/reproduction, and environmental impact to improve management (Berckmans, 2017), PLF has potential to dramatically transform the animal agricultural industry. Technologies utilised in PLF have tremendous potential to increase farm profitability, reduce labour needs, and create higher paying jobs in rural areas. Three main components encompass PLF activities:

1) machinery, equipment, and instrumentation (including drones, robots, sensors);
2) digital tools: data analytics, databases, and decision support systems;
3) and social and economic factors, including technology adoption, education, economics and workforce development.

Successful development and implementation of PLF technologies require a multidisciplinary approach involving experts in academia, industry, government and nongovernmental sectors. Governments play an essential role by establishing policies, supporting precompetitive research and facilitating translation of research by industry. To chart future investment opportunities in PLF from federal sources it is important to understand the role of government in R&D. Global spending on R&D has reached an all-time high with investments of 1.7 trillion USD (Unesco, 2019). The top 10 investing countries all have a high percentage (average 66%) of total R&D investments from the private business sector. Moreover, about 80 cents per dollar of private sector investment targets development to minimise risk (Hourihan & Parkes, 2016). The private sector performed 53% food and agriculture research in the U.S. in 2007 (USDA-ERS, 2012), and the economic return of public federal investments is estimated at 45% (USDA-ERS, 2008). High risk public investments are successful. For example, federally funded university researchers produce more high impact breakthroughs compared to projects funded from non-federal sources (Corredoira *et al.*, 2018). To maximise the impact of limited resources, federal investments must complement those of the private sector.

The United States maintains a robust federal agricultural research enterprise and educational programs through the U.S. Department of Agriculture's (USDA) intramural and extramural science, which helps to protect, secure and improve U.S. food, agricultural and natural resources systems. The USDA National Institute of Food and Agriculture (NIFA) is the USDA's primary extramural science agency that administers funding for programs to

advance agriculture-related sciences. NIFA is increasing its investment across precision agriculture disciplines through many programs. The goal of this study was to characterise the agency's contributions in PLF research and education and highlight potential areas of international collaboration. The results of this study may help chart the future directions in supporting PLF research and education at the federal and global level.

Materials and methods

U.S. federal landscape in precision agriculture

The U.S. federal investment in precision agriculture was characterised across various funding agencies using Federal RePORTER (https://federalreporter.nih.gov/), a U.S. federal repository that includes award information on more than one million projects funded by 18 federal science agencies between years 2006-2018, with the search term precision agriculture. A topic model is automatically generated based on word frequency in results.

NIFA investments and focus in PLF

The Cooperative Research Education & Extension Management System (CREEMS) internal NIFA database of competitively-funded projects was manually curated to identify PLF projects funded between years 2008-2018. The number of projects and total funding are reported. From projects, concepts were identified using a knowledge-discovery tool, Pushgraph®, (https://chalklabs.com/pushgraph/) (Herr II *et al.*, 2009). To generate the base map of NIFA-funded research reported in its Current Research Information System, the content of each grant was assessed using topic modeling, an unsupervised machine-learning method based on a modified latent Dirichlet allocation algorithm that uses statistics of co-occurring words in the grants' titles, keywords, and abstracts. Co-occurrence network relationships among terms in the corpus of analysed abstracts were constructed and visualised from text mining using VOSviewer (http://www.vosviewer.com/) (Van Eck & Waltman, 2011).

Opportunities in PLF at NIFA

The competitive grant programs at NIFA that represent opportunities for funding PLF science are summarised for the agency's Agriculture and Food Research Initiative (AFRI). Finally, current international partnerships are summarised to highlight potential collaborative opportunities between U.S. researchers and those around the world.

Results and discussion

U.S. federal landscape in precision agriculture

The U.S. federal investment in precision agriculture as reported by 18 science agencies in Federal RePORTER is over 106 million USD across 294 projects (Figure 2a,b). NIFA accounts for over 50% of the total awards (151/294) totalling 34 million USD with investments focused largely on crops and management systems (Figure 2a,b).

It is important to note that traditionally precision agriculture has referred to crops. Most scientific gatherings on PLF have taken place outside of the United States, with two recent events held here. A symposium entitled, 'Precision Livestock Farming to increase producers' profitability' was held at the American Association of Animal Science conference on 06 July 2018 (Moroto *et al.*, 2018) and another at Iowa State University entitled, 'Precision Livestock Farming Workshop' on 06 December 2018. One limitation in identifying relevant activity in PLF research is that researchers do not consistently use the same terminology. For example, researchers often use the term high-throughput phenotyping to describe technologies that take many measurements that could be used in management decisions such as breeding. One recommendation is for researchers to start using the term PLF more consistently. This would reduce duplication, allow effective portfolio analyses of investments and impacts, and help chart future directions in PLF effectively.

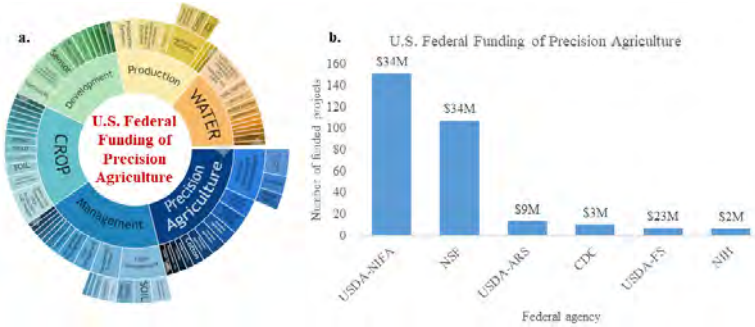

Figure 2. U.S. federal landscape in precision agriculture. a) A visualisation of data from Federal RePORTER indicates the precision agriculture topic themes across the top 3,500 relevant projects funded by 18 U.S. federal science agencies; b) A bar graph shows the number of funded projects in precision agriculture across six federal science agencies with data labels indicating the total investment in millions of U.S. dollars from 2006-2018. (NSF: National Science Foundation. ARS: Agricultural Research Service. CDC: Centers for Disease Control. FS: Forest Service. NIH: National Institutes of Health)

NIFA investments and focus in PLF

Manual curation of the CREEMS internal NIFA database revealed 50 projects funded in PLF totaling over 14 million USD from 2008-2018. The project titles, abstracts, and keywords were analysed using Pushgraph and VOS Viewer for concepts and terms to develop co-occurrence networks (Figure 3a,b) revealing disease/welfare was the major concept addressed in precision agriculture projects constituting 43% of the total. The co-occurrence networks revealed four major term clusters focused on health, emissions, detection methods and producers. The results focused on health is in alignment with EU-PLF efforts. Some examples of projects include dairy cattle lameness detection, pestiferous fly infestation modelling, and goat rumen bolus monitoring. Furthermore, emission/environment was the second largest concept area constituting 20% of funded projects, mainly ammonia sensors in the Small Business Innovation Research (SBIR) program. Recently, a grant in the Education and Workforce Development (EWD) program funded a project entitled 'Mentoring undergraduate students in precision livestock production for the 21st century.'

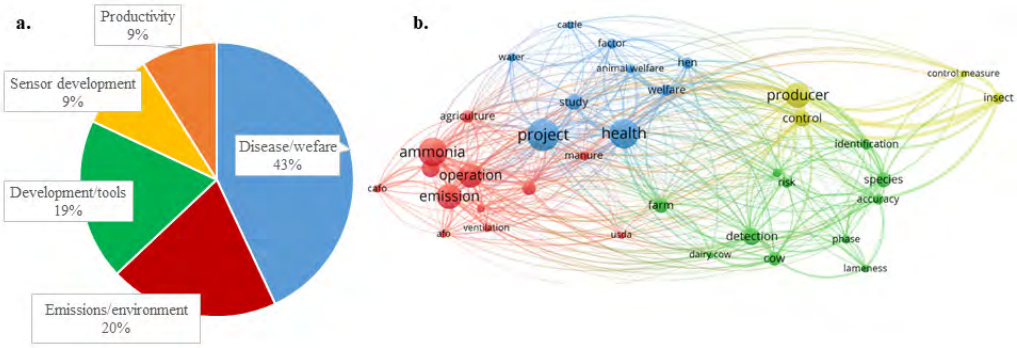

Figure 3. Concepts and network of NIFA's investments in PLF: a) Relative per cent effort in topics in PLF projects; b) Term map depicting relationships among topics in PLF projects. The size of circles indicates relative importance, colours indicate clusters of related terms, and the distance between two terms can be interpreted as an indication of the relatedness of the terms

Return on investments and new U.S. initiatives in PLF

The return on public investments in specific areas of research, education, and extension is difficult to quantify because of the diversity of funding sources, complex paths of innovation, and long timelines for most of applications. Across all agricultural fields the economic return of public federal investments is estimated at 45% (USDA-ERS, 2008). A 2017 report on NIFA-wide competitive grant funding illustrates impacts at the project level (https://nifa.usda.gov/sites/default/files/resource/NIFA-2017-Annual-Report.pdf). The adoption rates and U.S. federal investment of precision ag technologies are highest in cash crops (e.g. corn and soybean) with large acreages compared to livestock and specialty crops. This difference can be explained because of potential for high rates on return despite the substantial investments needed in the beginning. This presents an opportunity for high return on investments in PLF because public investments at this early stage of development and adoption may lower the risk for the industrial development of PLF technologies for the marketplace. New U.S. initiatives and programs may support future investments in PLF. For example, the recent U.S. Presidential Executive Order on Maintaining American Leadership on Artificial Intelligence (https://www.whitehouse.gov/presidential-actions/executive-order-maintaining-american-leadership-artificial-intelligence/) highlights the opportunities for AI in applications. The USDA recently launched the ReConnect program (https://www.usda.gov/reconnect/program-overview), and anticipates connectivity will be dramatically improved in rural areas of the U.S., including farmland. Finally, the USDA released the Animal Genome Blueprint for 2018-2027 (Rexroad, 2019) that includes goals focused on advancing PLF research.

Opportunities in PLF at NIFA

Numerous programs invest in or could potentially fund PLF research and education at NIFA mainly in AFRI (Table 1), NIFA's flagship extramural grants program.

Data, digital agriculture and artificial intelligence: NIFA has invested a significant amount in PLF disease and emissions work, however, the data generated by this work has yet to realise its full potential. Based on extensive engagement and stakeholder input, NIFA is increasing investments in data analytics and digital agriculture. To address the needs, NIFA launched the Food and Agriculture Cyberinformatics and Tools (FACT) program in 2017. Through the FACT initiative NIFA is investing 21 million USD across AFRI programs in FY2018. Decision tools for PLF and much-needed curated data for building those tools can be supported through the FACT program area.

Specialty products and livestock: NIFA invests in special commodity crops/animals that require new solutions and tools that industry has little incentive to tackle (e.g. fruits and vegetables, goats, and bees). Based on our analysis, most prior PLF work has focused on plants, revealing a critical need to invest in animal PLF.

Social, economic, educational, and workforce factors: NIFA is well equipped to fund efforts in the socio-economic realm (impacts, unintended consequences, perceptions, markets), including the impact of automation on labor needs. NIFA training programs span from informal methods (e.g. 4-H) to formal training at K-20 to Beginning Farmer & Rancher Development program. Training and workforce development are needed to move PLF innovations through the pipeline to the farmer.

The Department of Homeland Security reported only a few countries (China, Brazil, U.S., Australia, and those in the E.U.) currently have commercial facilities that use PLF (DHS, 2018). To make real progress in PLF global partnerships are required to leverage investments. Table 2 lists current international partnerships that could fund PLF efforts. These partnerships require contribution from both the U.S. and the other countries to fund scientists working outside the U.S.

Table 1. Main programs supporting precision livestock farming at the U.S. Department of Agriculture's National Institute of Food and Agriculture

	Agriculture and Food Research Initiative* program area	Description
Machinery, Equipment, and Instrumentation	Agriculture Systems and Technology	Blending of biological, physical, and social sciences to improve agriculture.
	Cyber-Physical Systems	Partnership with U.S. National Science Foundation that integrates computational algorithms and physical components.
	National Robotics Initiative	Partnership with multiple agencies to develop robots that work cooperatively with humans.
Digital	Critical Agricultural Research and Extension	Addresses critical challenges and opportunities that combine research and extension to improve agriculture.
	Critical Techniques, Technologies and Methodologies for Advancing Foundations and Applications of Big Data Sciences and Engineering	Partnership with NSF that funds novel approaches to further develop the interdisciplinary field of data science.
	Food and Agriculture Cyberinformatics Tools Initiative	Cross-cutting big data, analytics, and tool development.
Social, Economic, Education, and Workforce Factors	Agriculture Economics and Rural Communities	Promotes economically, socially, and environmentally sustainable agriculture and resilient rural communities.
	Education and Workforce Development	Addresses projected shortfalls in our agricultural graduates.

Table 2. International partnerships that could fund PLF at NIFA

Name	Country	Description
Partnerships for Enhanced Engagement in Research (PEER)	Multiple	Partnership between U.S. researchers with eligible NIFA awards can opt to partner with developing country scientists seeking to be funded by USAID.
Binational Agricultural Research and Development Fund (BARD)	Israel	Partnership between U.S. and Israeli scientists and engineers.
Ecology and Evolution of Infectious Disease (EEID)	U.K	Interagency program to address transmission dynamics of infectious diseases.
U.S.-Ireland Research and Development Partnership (Tripartite)	Ireland and Northern Ireland	Partnership to collaborate in developing solutions to priority challenges in agriculture.
Joint Programming Initiative on Antimicrobial Resistance (JPIAMR)	European consortium	Supports research projects and networks that enable U.S. and European researchers to tackle the global challenge of antimicrobial resistance.

Conclusions

In conclusion, USDA-NIFA is the primary federal agency supporting precision agriculture science activities in the United States. Traditionally, the primary focus of these activities was technologies associated with economically important crops, with relatively little investment in animal-related precision agriculture.

NIFA invested 14 million USD in 50 competitively-funded projects over the last decade. Of these, the major foci were concepts of health and disease, emissions, and tool development. More recently, significant needs were identified in collaboration with stakeholders to increase data analytics. Therefore, NIFA will be strategically investing in these efforts along with other relevant PLF needs. Most scientific gatherings on PLF have been held outside of the U.S., indicating a need for international collaborations.

As USDA moves forward with a focus on new technologies to increase profitability in American agriculture, it anticipates that there will be opportunities for collaborations in PLF. The work presented here is intended to help chart the future directions in supporting PLF research and education at the federal and global level.

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References

Alexandratos, N. & Bruinsma, J. (2012). World agriculture towards 2030/2050: the 2012 revision. ESA Working paper No. 12–03. Rome. FAO. http://www.fao.org/3/a-ap106e.pdf.

Berckmans, D. (2017). General introduction to precision livestock farming. *Animal Frontiers,* 7: 6–11.

Chan, C.Y., Tran, N., Dao, C.D., Sulser, T.B., Phillips, M.J., Batka, M., Wiebe, K. and Preston, N. (2017). Fish to 2050 in the ASEAN region. Working Paper: 2017–01. USA. IFPRI. http://pubs.iclarm.net/resource_centre/2017–01.pdf.

Corredoira, R.A., Goldfarb, B.D., Shi, Y. (2018). Federal funding and the rate and direction of inventive activity. *Research Policy,* 47: 1777–800.

DHS (2018). Threats to Precision Agriculture. https://www.dhs.gov/sites/default/files/publications/2018%20AEP_Threats_to_Precision_Agriculture.pdf.

FAO (2009). How to feed the world in 2050. High-level expert forum. http://www.fao.org/fileadmin/templates/wsfs/docs/expert_paper/How_to_Feed_the_World_in_2050.pdf.

FAO (2010). The state of food insecurity in the world, addressing food insecurity in protracted crises. Rome. http://www.fao.org/3/a-i1683e.pdf.

Herr II B.W., Talley, E.M., Burns, G., Newman, D., LaRowe G. (2009). NIH visual browser: an interactive visualization of biomedical research. *Proc 13th Int Conf Inform Visual*, 505–509.

Hourihan, M. & Parkes, D. (2016). Federal R&D budget trends: a short summary. https://www.aaas.org/news/federal-rd-budget-trends-summary.

Morota, G., Ventura, R.V., Silva, F.F., Koyama, M., Fernando, S.C. (2018). Big data analytics and precision animal agriculture symposium: Machine learning and data mining advance predictive big data analysis in precision animal agriculture. *Journal of Animal Science,* 96: 1540–50.

Rexroad, C. (2019). Genome to Phenome: Improving Animal Health, Production and Well-Being A New USDA Blueprint for Animal Genome Research 2018–2027. *Frontiers in Genetics*. In Press.

Unesco (2019). How much does your country invest in R&D http://uis.unesco.org/apps/visualisations/research-and-development-spending/.

USDA-ERS (2008). Agricultural research sustains productivity growth and earns high returns. https://

www.ers.usda.gov/amber-waves/2008/february/agricultural-research-sustains-productivity-growth-and-earns-high-returns/.

USDA-ERS (2012). The complementary roles of the public and private sectors in U.S. agricultural research and development. https://www.ers.usda.gov/publications/pub-details/?pubid=42861.

Van Eck, N.J. & Waltman, L. (2011). Text mining and visualization using VOSviewer. ISSI Newsletter, (paper, preprint, supplementary material). 7(3): 50–54.

Session 3

Precision Livestock Farming Sensing and Monitoring Techniques for Dairy Animals

Sensor technologies in dairy farms in Finland

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Abstract

This paper summarises the results of sensor technology status survey and questionnaire among medium and large dairy farms of Finland (N = 192). The purpose of the study was also to define specific needs and challenges related to on-farm milk fat/protein and on-farm silage composition analysers. Findings showed that responded Finnish medium-size dairy farms have high utilization rate of various on-farm sensor technologies. The importance vs present performance gap was high for the silage measurement solution and especially its response speed and accuracy. Similarly, the need is for accurate and fast milk fat/protein sensors, although the importance -performance gap depends significantly on the type of milking system used in the farm.

Keywords: sensor, milk composition, silage composition, analyser, automated milking system, milking parlour

Introduction

In modern dairy farms, sensors are key elements to control and monitor production in real-time for optimizing farm processes effectively. Sensors are primary data sources and enablers of modern data-based farm management and precision farming, in general. For the sensor development, it is vital to understand what dairy farmers want and what factors contribute to the market success. However, only few studies have been reported, such as a survey of sensor systems in Dutch dairy farms (Steeneveld & Hogeveen, 2015). In this study we conducted an overview of the sensor technology utilisation in large and medium-size dairy farms (> 50 cows) in Finland.

The sensors in dairy farms include e.g. mastitis, ketose, estrus, progesterone, milk physical properties and composition, somatic cell counters as well as wearable activity sensors such as for heat, movement and rumination. In addition to overview of sensor utilisation in Finland, our emphasis in this study is to understand farmers needs related to on-farm sensor technologies for feed and milk composition.

Namely, today in Finland, the milk and feed composition analyses rely predominantly on laboratory services and not on farm deployable sensors nor real-time data. The laboratory analyses requires sampling and sending the samples to the laboratories causing labour and other costs, time delays and potentially unrepresentative sampling. Many of these challenges could be overcome by on-farm measurements.

The commercial laboratories conduct the feed and milk analyses using typically Near-infrared spectroscopy (NIRS) with laboratory validated methodology of quantitative analyses (e.g. Nousiainen *et al.*, 2004). The recent development of miniaturised NIRS components and instrumentation technology has facilitated low cost sensors with continuously improved accuracy for field deployable and on-farm use scenarios (e.g. Malinen *et al.,* 2014). Therefore, in this study, we focused on identifying market success factors for the on-farm NIRS sensor development for milk and feed composition.

Material and methods

Data collection

Data collection method was a web-based survey and questionnaire executed in spring 2018 and targeted to 1,000 randomly chosen Finnish dairy farms with > 50 cows. The mailing list was generated from Faba (cooperative corporation, livestock owner's breeding service provider in Finland) customer base which covers > 90% dairy farms in Finland. By narrowing the target group by herd size, the survey consciously aimed at reaching modern and developing farms.

Responder statistics (compared to average Finnish dairy farms)

The responded farms (N = 192) represented geographical distribution of Finnish dairy farms i.e. were predominantly located in Central and Eastern Finland. Responded farms had < 70 cows (45%), 70 - 120 cows (31%) and > 120 cows (23%), while national average is 36.8 cows (Luke, 2019). The annual energy corrected milk production was 8,000–10,000 (38%), 10,000–12,000 (56%) and > 12,000 (6%) kg, while national statistics average was 9,239 kg ECM per year in 2017. Organic milk producers were not distinguished in this survey (c. 3% of cows in Finland, 2017).

Official lab-service based milk yield recording was utilised by 93% of responders (81% on average in Finland, Nokka, 2018). The responders stated that 70% of them had an automated milking system (AMS) and 20% had a milking parlour. Survey also identified the AMS supplier and shared by Lely (55%), DeLaval (40%) and others (4%). In addition, 73% of responders stated they produced silage by themselves, while contracting in various ways employed 42%.

Importance - Performance gap analysis

As a special questionnaire methodology we used importance - performance gap analysis (IPA), introduced originally by Martilla and James (1977) for market research. The method is initially developed to identify which attributes of any product or service should be improved to become more competitive in the market. Although it is widely usable method, it has not been employed much to evaluate market needs for new technological opportunities. In this study, the IPA method was carried out to identify farmer needs separately for milk fat/protein and for silage dry matter and protein analysis. The asked attributes also contained speed and accuracy of these measurements. The responders were asked to score the attributes separately for importance and performance. The importance-performance gap is determined as X = Y - Z, where X is the gap, Y is importance and Z is performance. The higher the gap value, in the relative data set, the higher is the need.

Results and discussion

Sensor utilisation status

Table 1 summarises the result of sensor use on dairy farms. Of the responders, 97% used at least one sensor from the given options. The highest overall sensor utilisation was with milk physical properties (conductance, colour, temperature), somatic cell count and cow activity. The segmented comparison between AMS and milking parlour is illustrated in Figure 1. The AMS users dominate the sensor utilisation, especially when it comes to milk property related sensors. Notable is that in the cases of silage moisture and composition measurements, rapid tests and activity meters, also milking parlour system users appeared to be active.

Table 1. Data from survey responses to the question: What sensors and measurement devices are in use on the farm? Responder chose from the given options as listed

Sensor item	Number of farms (N =192)	Percentage of farms (%)
Milk conductance	143	75.0
Activity meter (incl. heat)	140	73.4
Milk temperature	137	71.4
Milk colour	111	58.3
Somatic cell count	100	52.6
Rapid tests (progesterone, etc.)	76	39.6
Milk fat/protein	70	36.5
Rumination measurement	67	34.9
Animal weight	67	34.9
Eating time	20	10.4
Silage moisture	10	5.2
Silage composition (NIR, etc)	6	3.1
HerdNavigator (DeLaval)	5	2.6
Automated body condition score	2	1.0

The responses to the question "What has been the most important reason to invest in sensor or measurement device?" is illustrated in Figure 2. The most important reason to invest had been to improve the detection of cow disorders and heat and secondly to help in optimising the production. Multiple choices were allowed, and milking parlour users found less attributes in general than AMS users.

Economical impact expectations

We asked how satisfied the responder was for the profitability of the farm (scale ranging from 1–5, where 1 = not at all satisfied, 2 = not much satisfied, 3 = to some extent satisfied, 4 = satisfied and 5 = very satisfied). Of all responders, only 25% were satisfied (considering answers four and five). We compared the profitability satisfaction to other survey questions. Any specific sensor uses were not related to profitability satisfaction. Satisfaction was also not related to the milking system type, herd size or any other asked practices, like silage production. However, the relation was clear with average annual milk production.

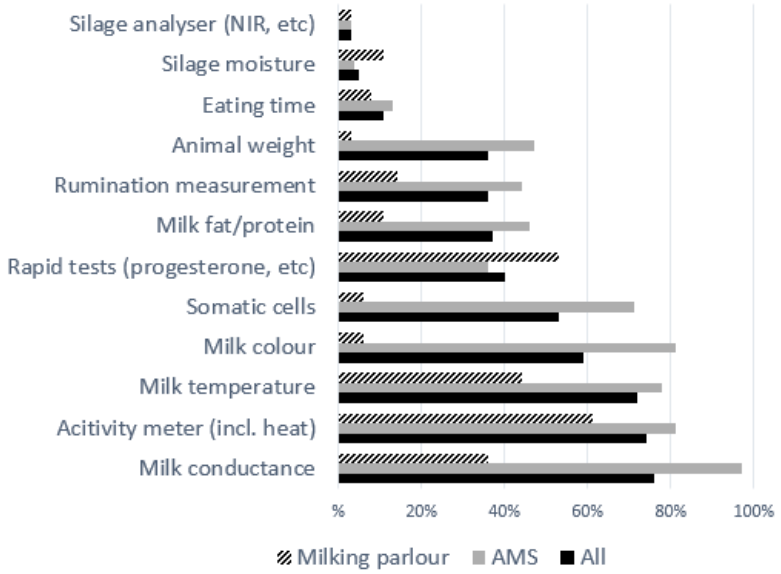

Figure 1. Graphical comparison of the sensor use on Finnish dairy farms with AMS and milking parlour system and all responders

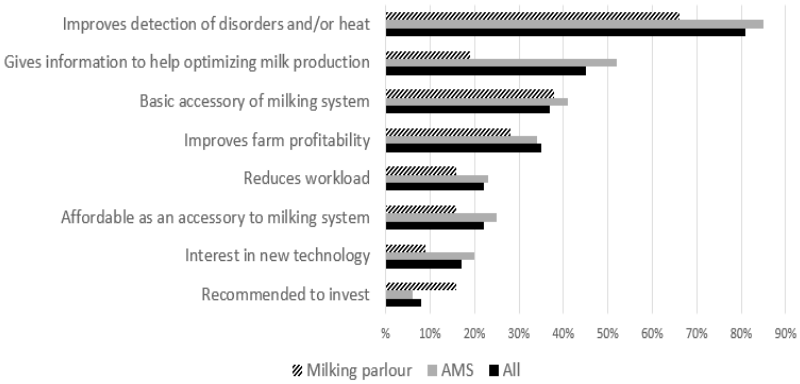

Figure 2. Percentages of farms responding to the question: What has been the most important reason to invest in sensors? (Data from all responders, AMS users and milking parlour system users illustrated separately)

We continued by asking what responders considered to be the most important ways to improve profitability by proposing options which are related to certain sensing needs. This result is given in Table 2.

As shown, the highest expectations to improve profitability were based on improving protein and fat content in milk. On the other hand, it is notable that the milk fat/protein sensors were in use only in 36.5% of the farms (Table 1).

Table 2. Data from survey responses to the question: What are the four most important ways to improve profitability? Responders chose from the given options as listed

Proposed way to improve profitability	Number of farms (N = 192)	Percentage of farms (%)
Increase fat and protein content in milk	125	65
Increase amount of milk	116	61
More effective preventive animal healthcare	96	50
Improve animal wellbeing	92	48
Improve silage energy content	86	45
Better udder health	80	42
Better foot health	47	25
Increase voluntary feed intake	42	22
Avoid ketosis	36	19
Better control of silage dry-matter content	33	17
Better access to advisor services	8	5

Those who had the milk fat/protein sensor (36.5%, N = 70, Table 1) were predominantly using AMS (88%, N = 62) and especially Lely system (81%, N = 57). The Lely AMS has an accessory of an optical sensor that measures milk fat/protein on-line. In the free word part, the Lely AMS users comments were as follows:

- 'There are no problems with the sensors, but in the official milk recording practices. The robot and milk tank analyses are in line with each other, but official milk recording shows lower milk fat content and nobody knows why.'
- 'Official milk recording system should use the information from the robot. The amount of samples beats the quality of analysis. One sample vs 180 samples!'

The silage moisture and composition sensing was used quite rarely on farms (8%, N = 16) and contrary to milk fat/protein sensors, did not indicate any relation to any specific milking system (AMS or parlour).

Importance - performance gap analysis for milk and silage sensors

The last part of the study focused on specific needs and challenges related to milk fat/protein sensors and silage moisture and protein sensors. This was performed by using importance - performance gap analysis. At first, we asked responders to score from one to five the importance of the given attributes and right after that, to score the same attributes, to the question: how satisfied was the responder with the present performance on the farm.

The asked attributes and the gap analysis results are summarised in Tables 3 and 4. The higher the number, the higher the gap, meaning the higher the need to solve that particular attribute and perform development actions.

In the case of milk fat/protein sensors, clear differences can be seen between Lely and DeLaval AMS users. Lely AMS users have less overall need for milk fat/protein sensor than DeLaval AMS or milking parlour users. Of the specific attributes, Lely AMS users express a high need for better accuracy for the milk composition measurement.

Overall, the silage dry matter and protein content measurement needs (Table 4) are higher

than for milk composition (Table 3), reflecting the challenges in present laboratory services and/or lack of compelling, usable or affordable silage composition sensor solutions for on-farm use.

Table 3. Importance-performance gap values for milk composition measurement attributes for all responses and for various milking system users

Milk composition sensor	All (N=192)	AMS (N=135)	Milking parlour (N=38)	AMS Lely (N=78)	AMS DeLaval (N=54)
Measuring fat and protein content in milk	0.38	0.38	0.45	0.22	0.56
Speed to gain the measurement data	0.40	0.44	0.34	0.17	0.86
Accuracy of the measurement data	0.57	0.60	0.52	0.49	0.72
Total Average	0.45	0.47	0.44	0.29	0.71

Table 4. Importance - performance gap values for silage composition measurement attributes for all responses and for various milking system users

Silage composition sensor	All (N=192)	AMS (N=135)	Milking parlour (N=38)	AMS Lely (N=78)	AMS DeLaval (N=54)
Measuring dry matter content of silage	0.55	0.59	0.45	0.71	0.42
Measuring protein content of silage	0.54	0.61	0.37	0.58	0.64
Speed to gain the measurement data	0.86	1.01	0.63	1.08	0.95
Accuracy of the measurement data	0.80	0.87	0.71	0.88	0.83
Total Average	0.69	0.77	0.54	0.82	0.71

Manual operations for the measurements

Many optical spectrometry based sensors, which can be useful in silage and milk composition measurements, often require maintenance such as calibration. Also, sampling is crucial to gain high accuracy. Namely, silage is heterogeneous material and quantitative accuracy will depend on e.g. sample quality and sample amount. Sampling is also important in the case of milk samples, e.g. temperature and time can influence the accuracy of the results. The usability of the sensor can be significantly improved by automating such practices. However, in the sensor development point of view, such automated operations on farms can be challenging to implement and therefore we asked whether the user is willing to perform manual operations to gain more accurate and faster results. The answers were:

YES: 58% (N = 122)
NO: 30% (N = 55)
YES, if: 12%, (N = 15)

where *yes, if* -answers emphasised the ease of such operations including frequency (less than once a week), clear instructions and reminders sent automatically to phone by e.g. text messages. Since 70% of responders were willing to perform manual operations, this result also reflects the need for real-time information of silage composition.

Conclusions

Finnish dairy farms have high utilisation rate of sensors and awareness of technical opportunities to improve farm productivity.

AMS supplier was an important factor when defining specific sensor needs on farms, as shown in this survey especially through milk fat/protein sensors comparison between Lely and DeLaval AMS users.

The purpose of the study was also to define specific needs and challenges related to on-farm milk fat/protein and silage dry matter and protein sensor development The importance -performance gap analysis clearly indicated the need for accurate, fast response and on-farm usable sensor solutions for milk and feed composition control and monitoring.

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References

Luke (2019). Statistics database. Available at: https://stat.luke.fi/en/.

Malinen, J., Rissanen, A., Saari, H., Karioja, P., Karppinen, M., Aalto, T., and Tukkiniemi, K. (2014). Advances in miniature spectrometer and sensor development. In: *Proceedings Volume 9101, Next-Generation Spectroscopic Technologies VII; 91010C: SPIE Sensing Technology + Applications,* Baltimore, Maryland, United States.

Martilla, J.A. and James, J.C. (1977). Importance-Performance Analysis, *Journal of Marketing*, 41: 77–79.

Nokka, S. (2018). Tuotosseurannan tulokset 2017, *Maidon ja nurmentuotannon tulosseminaari 2018*, Vantaa, Finland.

Nousiainen, J. Ahvenjärvi, S., Rinne, M., Hellämäki, M. & Huhtanen, P. (2004). Prediction of indigestible cell wall fraction of grass silage by near infrared reflectance spectroscopy *Animal Feed Science and Technology,* 115: 295–311.

Steeneveld, W. and Hogeveen, H. (2015). Characterization of Dutch dairy farms using sensor systems for cow management, *Journal of Dairy Science,* 98: 709–717, http://dx.doi.org/ 10.3168/jds.2014–859.

The use of infrared reflectance spectroscopy to predict the dry matter intake of lactating grazing dairy cows

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Abstract

Monitoring the feed efficiency of grazing dairy cows is currently restricted by lack of a quick, cost effective and accurate method to estimate dry matter intake (DMI). The aim of this study was to compare Near Infrared Reflectance Spectroscopy (NIRS) analysis of faeces and Mid Infrared Reflectance Spectroscopy (MIRS) analysis of milk to predict the DMI of lactating grazing dairy cows. Faecal samples were obtained from four different grazing experiments where DMI had been estimated using the n-alkane technique resulting in a dataset of 1,083 cows. Equations were developed using the following variables; 1) milk yield (MY), fat %, protein %, body weight (BW), stage of lactation (SOL) and parity, which was used as a benchmark to which the following could be compared; 2) MIRS wavelengths, 3) MIRS wavelengths, MY, fat %, protein %, BW, SOL and parity, 4) NIRS wavelengths, 5) NIRS wavelengths, MY, fat %, protein %, BW, SOL and parity. The benchmark equation was more accurate (coefficient of determination (R^2) = 0.61; root mean square error (RMSE) = 1.68 kg) than MIRS wavelengths alone (R^2 = 0.28; RMSE = 2.27 kg) or NIRS wavelengths alone (R^2 = 0.15; RMSE = 2.45 kg). The combination of the benchmark equation with MIRS wavelengths (R^2 = 0.64; RMSE = 1.58 kg) resulted in slightly more accurate predictions than the benchmark equation alone. The combination of the benchmark equation with NIRS wavelengths (R^2 = 0.59; RMSE = 1.48 kg) did not result in more accurate predictions than the benchmark equation.

Key words: dry matter intake, near-infrared reflectance spectroscopy, mid-infrared reflectance spectroscopy, grazing dairy cows

Introduction

Feed efficiency is an important component of dairy systems (Berry and Crowley, 2013; Connor, 2014). A major obstacle to the inclusion of feed efficiency as a component in dairy breeding programmes is routine access to individual animal feed intake data (Connor, 2014). In grazing systems, the measurement of individual animal feed intake is a difficult task (Coleman, 2005). The n-alkane technique (Mayes *et al.*, 1986; Dillon and Stakelum, 1989) is commonly used to estimate dietary dry matter intake (DMI) in grazing dairy cows (Hurley *et al.*, 2017). However, this method is expensive to employ and labour intensive, thus is only applicable under research conditions.

The ability of MIRS analysis of milk to estimate the intake of dairy cows has recently been documented (McParland *et al.*, 2014; Shetty *et al.*, 2016). Similarly, NIRS analysis of faeces has been reported as a potentially useful method of estimating intake (Boval *et al.*, 2004). A direct comparison among these methods to predict the DMI of grazing dairy cows would elucidate their accuracy, robustness and applicability for use on commercial dairy farms.

The objective of this study was to evaluate the ability of MIRS of milk compared with NIRS of faeces and in combination with one another, to predict the DMI of grazing dairy cows.

Materials and methods

A faecal sample set comprising 1,083 samples with corresponding DMI values from 449

individual spring calving Holstein-Friesian and Holstein-Friesian × Jersey cross bred cows were available from four grazing research experiments (Kennedy *et al.*, 2015; McCarthy *et al.*, 2015; Coffey *et al.*, 2017; O'Sullivan *et al.*, 2019) conducted by Teagasc, Animal & Grassland Innovation Centre, Moorepark, Fermoy, Co. Cork, Ireland. Individual herbage DMI was estimated within each experiment using the *n*-alkane technique and faecal grab samples (Mayes *et al.*, 1986) as modified by Dillon and Stakelum (1989). The diet of the cows during the *n*-alkane measurement period consisted predominantly of grazed pasture *(Lolium perenne* L.*)*.

Near infrared reflectance values of the bulked faecal samples from each intake estimation period were gathered using a FOSS-NIRSystem 6500 SYII scanning monochromator (FOSS-NIRSystems, Silver spring, MD, USA). Rectangular quartz cells (4.6 cm wide and 5.7 cm long) were used to scan each faecal sample. The spectral absorbance value of each faecal sample was recorded as log/reflectance values over the wavelength range of 1,100-2,496 nm giving 699 individual data points. The spectral data points between 1,200-2,496 nm were retained for analysis.

Throughout each DMI estimation period, body weight (BW) was recorded once following morning milking using calibrated weighing scales. Individual cow milk yield (MY) was recorded twice daily throughout the intake estimation period using electronic milk meters (Dairymaster, Causeway, Co. Kerry, Ireland). Milk was sampled from consecutive evening and morning milking's once weekly during each intake estimation period. These samples were analysed using a FOSS Milkoscan FT6000 spectrometer (Foss Electric A/S, Hillerød, Denmark) to determine fat and protein content. The milk mid-infrared spectral data were subsequently stored for further analysis. The spectral data points between 925-1,620 and 1,727-3,043 cm^{-1} were retained for analysis.

Animals of third parity plus were grouped together. Additionally, stage of lactation (SOL) was defined as: 1) < 49, 2) 50-99, 3) 100-189, and 4) > 190 days in milk.

Prediction Equations

Equations to predict DMI were developed using the following variables; 1) MY, fat %, protein %, BW, SOL and parity, which was used as a benchmark to which the following could be compared: 2) MIRS wavelengths, 3) MIRS wavelengths, MY, fat %, protein %, BW, SOL and parity, 4) NIRS wavelengths, 5) NIRS wavelengths, MY, fat %, protein %, BW, SOL and parity. Linear regression was used to develop equation 1 while partial least squares regression (PLS; PROC PLS; SAS Institute Inc., Cary NC) was used to develop all other equations. Split-sample cross-validation was initially undertaken on all PLS models and involved removing every 20th sample from the data set and predicting it using data from the remaining data set. This was repeated until every sample had been predicted once. Equations were subsequently validated across herds.

Across herd validation was undertaken to assess if equations could predict the DMI of an independent group of experimental animals. This was undertaken by using three out of the four experiments to develop the models, while the remaining experiment was used for external validation. This was iterated until each herd had been predicted once. The following metrics were used to assess the accuracy and robustness of the models; the coefficient of determination (R^2), the root mean square error (RMSE), the mean bias of prediction, the regression coefficient (slope), the mean R^2 and RMSE factors were reported as the average of the four iterations of across herd validation, the mean bias and slope were reported as the range of values across the four iterations.

Results and discussion

Mean values (± SD in parenthesis) of DMI, MY, fat %, protein %, lactose %, BW, parity and DIM across the data set were 15.6 kg/d (3.1), 20.4 kg/day (5.4), 4.5% (0.7), 3.7% (0.4), 4.8 (0.2)

498 kg (69), 2.0 (0.8) and 123 (64), respectively.

Table 1 presents the fitting statistics for all five equations to predict DMI upon across herd validation. The benchmark equation resulted in an R^2 of 0.61, and a RMSE of 1.68 kg. The strong prediction by the benchmark equation is supported by previous studies (O'Neill *et al.*, 2013; McCarthy *et al.,* 2014).

Table 1. Fitting statistics[1] of cross- and across herd validation prediction equations to predict dry matter intake

	Cross-validation		Across herd validation			
Variables[2]	**RMSE**	**R^2**	**Bias**	**RMSE**	**Slope (SE)**	**R^2**
MY F% P % BW parity SOL[3]	1.63	0.72	0.49 to -0.67	1.68	1.11* (0.04) to 0.69* (0.04)	0.61
MIRS	2.06	0.56	1.71 to -0.43	2.27	0.73* (0.06) to 0.51* (0.13)	0.28
MIRS F% P % MY BW parity SOL	1.40	0.79	0.44 to -0.52	1.58	1.01 (0.03) to 0.65* (0.12)	0.64
NIRS	1.92	0.61	2.57 to -1.61	2.45	0.64* (0.12) to -0.06* (0.04)	0.15
NIRS MY F% P % BW parity SOL	1.42	0.79	1.36 to -0.50	1.71	1.08* (0.04) to 0.75* (0.04)	0.59

[1]RMSE = average root mean square error from the four iterations of cross and across herd validation; R^2= average coefficient of determination from the four iterations of cross and across herd validation; RPD = average ratio performance deviation from the four iterations of across herd validation; Bias = range of highest to lowest values from the four iterations across herd validation; Slope = range of highest to lowest value from the four iterations of across herd validation; [2]MY = Milk yield; F% = fat %; P% = protein %; SOL = Stage of lactation; BW = body weight; MIRS = Mid-infrared reflectance spectroscopy analysis of milk; NIRS = Near-infrared reflectance spectroscopy analysis of faeces; [3]Developed using linear regression; *Slope test ($b \neq 1$; $P < 0.05$)

The use of MIRS wavelengths alone to predict DMI resulted in inferior fitting statistics compared to the benchmark equation, with an R^2 of 0.28 and a RMSE of 2.27 kg. Combining MIRS wavelengths with the variables in the benchmark equation resulted in slightly superior fitting statistics compared to the benchmark equation alone, with an R^2 of 0.64 and a RMSE of 1.58 kg. The use of NIRS wavelengths alone to predict DMI resulted in a mean R^2 of 0.15 and a RMSE of 2.45 kg. The combination of NIRS wavelengths with the variables in the benchmark equation did not result in superior fitting statistics than the benchmark equation, with an R^2 of 0.59 and a RMSE of 1.71 kg.

Methods of predicting DMI for the purposes of improving feed efficiency must be easily deployed in commercial settings. Milk samples from commercial farms are currently analysed using MIRS to determine milk constituents (McParland *et al.,* 2014). Therefore, the combination of MIRS wavelengths with the variables in the benchmark equation is suitable for predicting DMI in grazing dairy cows to improve feed efficiency.

Conclusions

This study confirms the potential that exists for both MIRS and NIRS analysis to predict the DMI of lactating dairy cows under grazing conditions. The two methods provide additional information relating to feed intake over and above the benchmark equation. The use of MIRS analysis of milk in combination with the variables MY, fat %, protein %, BW, SOL and parity is the most accurate method for the collection of phenotypic feed intake data.

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References

Berry, D.P. and J.J. Crowley. (2013). Genetics of feed efficiency in dairy and beef cattle. *J Anim. Sci*., 91(4): 1594–1613.

Boval, M., D.B. Coates, P. Lecomte, V. Decruyenaere, and H. Archimède. (2004). Faecal near infrared reflectance spectroscopy (NIRS) to assess chemical composition, in vivo digestibility and intake of tropical grass by Creole cattle. *Anim. Feed Sci. Tech*., 114(1): 19–29.

Coffey, E.L., L. Delaby, S. Fitzgerald, N. Galvin, K.M. Pierce, and B. Horan. (2017). Effect of stocking rate and animal genotype on dry matter intake, milk production, body weight, and body condition score in spring-calving, grass-fed dairy cows. *Journal of* Dairy Science, 100(9): 7556–7568.

Coleman, S.W. (2005). Predicting forage intake by grazing ruminants. Pages 72-90 in Proceedings of 2005 ruminanat nutrition symposium, Florida.

Connor, E.E. (2014). Invited review: Improving feed efficiency in dairy production: challenges and possibilities. *Animal*, 9(3): 395–408.

Dillon, P. and G. Stakelum. (1989). Herbage and dosed alkanes as a grass management technique for dairy cows. *Irish J Agric. Res*., 8: 104.

Hurley, A.M., N. López-Villalobos, S. McParland, E. Lewis, E. Kennedy, M. O'Donovan, J.L. Burke, and D.P. Berry. (2017). Genetics of alternative definitions of feed efficiency in grazing lactating dairy cows. *Journal of* Dairy Science, 100(7): 5501–5514.

Kennedy, E., L. Delaby, B. Horan, J. Roche, and E. Lewis. (2015). Duration is important in the effect of pasture allowance restriction on subsequent milk production, in early lactation. Grassland and forages in high output dairy farming syatems, 2015 Wagenignen, the Netherlands. European Grassland Federation EGF, 110–112.

Mayes, R., C. Lamb, and P.M. Colgrove. (1986). The use of dosed and herbage n-alkanes as markers for the determination of herbage intake. *J Agric. Sci.,* 107(01): 161–170.

McCarthy, B., M. Dineen, C. Guy, F. Coughlan, and T. Gilliland. (2015) The effect of tetraploid and diploid perennial ryegrass swards sown with and without clover on milk and herbage production. Grassland and forages in high output dairy farming systems, 2015 Wagenignen, the Netherlands. European Grassland Federation EGF, 259–261.

McCarthy, J., B. McCarthy, B. Horan, K. Pierce, N. Galvin, A. Brennan, and L. Delaby. (2014). Effect of stocking rate and calving date on dry matter intake, milk production, body weight, and body condition score in spring-calving, grass-fed dairy cows. *Journal of* Dairy Science, 97(3): 1693–1706.

McParland, S., E. Lewis, E. Kennedy, S.G. Moore, B. McCarthy, M. O'Donovan, S.T. Butler, J.E. Pryce, and D.P. Berry. (2014). Mid-infrared spectrometry of milk as a predictor of energy intake and efficiency in lactating dairy cows. *Journal of* Dairy Science, 97(9): 5863–5871.

O'Neill, B.F., E. Lewis, M. O'Donovan, L. Shalloo, F.J. Mulligan, T.M. Boland, and R. Delagarde. (2013). Evaluation of the GrazeIn model of grass dry-matter intake and milk production prediction for dairy cows in temperate grass-based production systems. 2 – Animal characteristics. *Grass For. Sci*., 68(4): 524–536.

O'Sullivan, M., Horan, B., Pierce, K.M., McParland, S., O'Sullivan, K. & Buckley, F. (in press). Milk production of Holstein-Friesian cows of divergent Economic Breeding Index evaluated under seasonal pasture-based management. *Journal of* Dairy Science In Press. https://doi.org/10.3168/jds.2018–15559.

Shetty, N., P. Løvendahl, M.S. Lund, and A.J. Buitenhuis. (2016). Prediction and validation of residual feed intake and dry matter intake in Danish lactating dairy cows using mid-infrared spectroscopy of milk. *Journal of* Dairy Science, 100(1): 253–264.

Soyeurt, H., F. Dehareng, N. Gengler, S. McParland, E. Wall, D.P. Berry, M. Coffey, and P. Dardenne. (2011). Mid-infrared prediction of bovine milk fatty acids across multiple breeds, production systems, and countries. *Journal of* Dairy Science, 94(4): 1657–1667.

Monitoring enteric methane emissions and intake dynamic in grazing ruminants

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Abstract

Livestock is a significant source of anthropogenic greenhouse gasses (GHG) emissions. Enteric methane (CH_4) from ruminants is one of the most relevant sources of GHG in this sector. There are several methods to measure CH_4 emissions in ruminants, but these methods are expensive and demand highly skilled labour which limits its utilisation, especially in developing countries. Alternatively, less accurate but inexpensive and easy to implement methods can be used. We developed a sensor-based device for studying enteric CH_4 emissions and intake dynamics in grazing ruminants. The principle behind our device is a constant data recording from two sensors, a three-axis accelerometer which detects animal's head positions, and a semiconductor which detects CH_4 concentration changes in ruminants' breath. A three-dimensional accelerometer (MPU6050), is used to detect if the animal bowed its head to eat or not, and a CH_4 gas sensor (MQ4) was connected to an Arduino board. To guarantee that the MQ4 sensor can detect CH_4 concentration changes in animals' breath, an air sampler system was added. A halter was used to place the device at the back side of the animal's head and to place the air collector near to the animal's mouth. For 24 hours of uninterrupted recordings, the device was powered by a rechargeable 5V, 50000 mAh lithium-ion battery. Our device shows that the CH_4 concentration in ruminant's breath increases when animals are eating. This result probably means that intake behaviour, measured with accelerometers, can be used to estimate CH_4 emissions in grazing ruminants.

Keywords: Arduino, MQ4, accelerometer, grazing cattle

Introduction

Enteric methane (CH_4), generated in the gastrointestinal tract of domestic animals, is the single largest source of anthropogenic CH_4 emissions (Knapp *et al.,* 2014). Methane is mainly produced in the rumen by Archaea microorganisms as a by-product of fermentation. Methane emission results in 3 - 14% loss in gross energy intake (Hellwing *et al.*, 2016), and increases atmospheric GHG concentrations, which causes global climate changes and adverse phenomena such as floods and droughts, modifications in level and patterns of precipitation, and heat waves in cities (La Notte *et al.*, 2018).

Open-circuit respiration chambers (Waghorn, 2014) are recognised as the most accurate method to measure enteric CH_4 emissions whereas the sulfur hexafluoride tracer technique (SF6, Johnson *et al.,* 2007) and the automated head-chamber system (GreenFeed, Zimmerman & Zimmerman, 2012) are accepted as methods to estimate CH_4 emission. The use of these methods is expensive and demands highly skilled labour which limits utilisation, especially in developing countries. Alternatively, less accurate and certain methods have been developed. One approach uses CO_2 emission and CO_2:CH_4 ratio in exhaled air by animals to estimate CH_4 (Madsen *et al.*, 2010). Another method is the Laser CH_4 Detector (Chagunda & Yan, 2011), in which CH_4 concentration in the air between the device and the animal is measured.

Accelerometers are useful tools to measure animal behaviour. Accelerometers are electronic sensors used to monitoring animal movement, such as feeding behaviour (Mattachini, 2016). Because of the operational utility of accelerometers and given that enteric CH_4 emissions have a clear dynamic related to intake pattern, with a rapid increase in emissions after feeding followed by a gradual decline (Noguera & Posada, 2017), accelerometers could also be used to estimate enteric CH_4 emissions. The aim of this work was to develop a low-cost, sensor-based device to study the daily dynamic of enteric CH_4 emission and intake in grazing ruminants.

Materials and methods

The device

The device was developed as a non-invasive, sensor-based system for monitoring intake behaviour and enteric CH_4 emissions. The principle behind the device is constant data recording from two sensors, which determine the animal's head position and CH_4 concentration changes in ruminant's breath. The head position analysis is used to establish feeding behaviour.

Electronic components and connections

A CH_4 gas sensor (MQ4) and a three-dimensional accelerometer (MPU6050) was connected to an Arduino board (Figure 1). The MQ4 sensor was connected to analogue pin A0 and the accelerometer was connected to A4 and A5 pins. To store sensors data in a text file, a micro SD card module was also connected (MOSI in pin 11, MISO in pin 12, CLK-SLK in pin 13, and CS in pin 10).

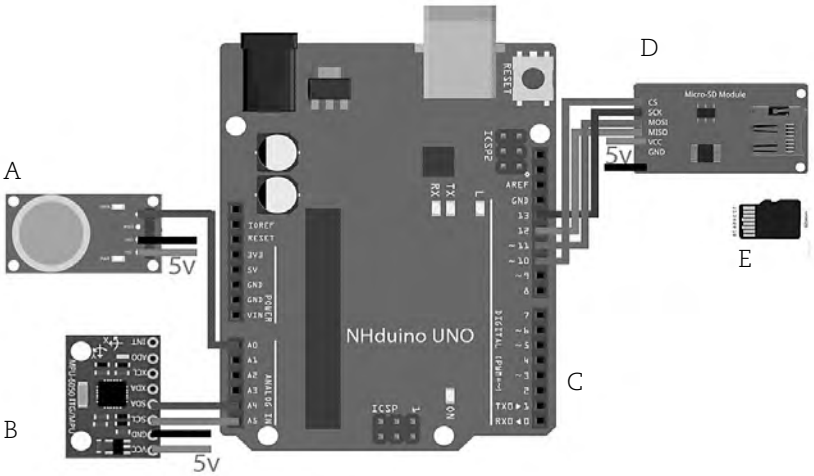

Figure 1. Device components and connections
(A) MQ4 sensor, (B) Accelerometer, (C) Arduino board, (D) SD card module, and (E) SD card

MQ4 sensors are composed by micro-ceramic tube, Tin Dioxide (SnO_2) sensitive layer, measuring electrode and heater, are all fixed into a crust made by plastic and stainless steel net. Every MQ4 sensor has six pins, two of them are used to provide heating current and the remaining four used in signal fetching (Vinaya *et al.,* 2017). MPU6050 is a compact motion processing technology. It consists of a 3-axis gyroscope and a 3-axis accelerometer. The three axes are present to acquire the magnitude and direction of acceleration and orientation. Accelerometer and Gyroscope are combined on a single silicon chip with an onboard digital processor (Prince *et al.,* 2014).

Assembly

The electronic components were placed inside a plastic box (Figure 2A). The accelerometer was fixed inside the box. To guarantee that the MQ4 sensor can detect CH_4 concentration changes in ruminant's breath, an air sampler system was added. An electric air pump and a plastic tube create a constant airflow from the animal's muzzle area to the plastic box. The MQ4 sensor, hermetically placed on a plastic capsule, comes in contact with the airflow (Figure 2B) before that air sample leaves the device. A halter, which does not affect the ruminant's well-being, was used to place the device at the back side of animal's head and to place the air collector near to the animal's mouth (Figure 2C). The device was powered by a rechargeable 5V, 50000 mAh lithium-ion battery which allows up to 24 hours of uninterrupted recordings.

Figure 2. (A) The Device (Electronic components inside a 100x68x50mm box), (B) Air sampler system, and (C) A cow wearing the device

Coding

The device executes a code written in the Arduino IDE (Appendix 1). TimeLib, MPU60580 and SD libraries were included to set time, read raw data from the accelerometer and store information in the SD card, respectively. In the *Setup* function, the port for storing data and the accelerometer are initialized and a text file, with each variables name, is created. In the *Loop* function, time and sensors data are written in the text file as a new line every second. Time is reset every time the device is restarted. To keep time and date after device restart, a Real Time Clock Module is required.

Results and discussion

Both the accelerometer position inside the device and the device position on the animal, allows the ruminant's feeding behaviour to be studied using changes in just one accelerometer axis. The plot of the CH_4 concentration in the animal's breath (Figure 3A)

and the accelerometer changes related to eating activity (Figure 3B) showed that there is a high concordance between both dynamics across time. It means that our device allows corroborating that CH_4 concentration in ruminant's breath increases when the animals are eating.

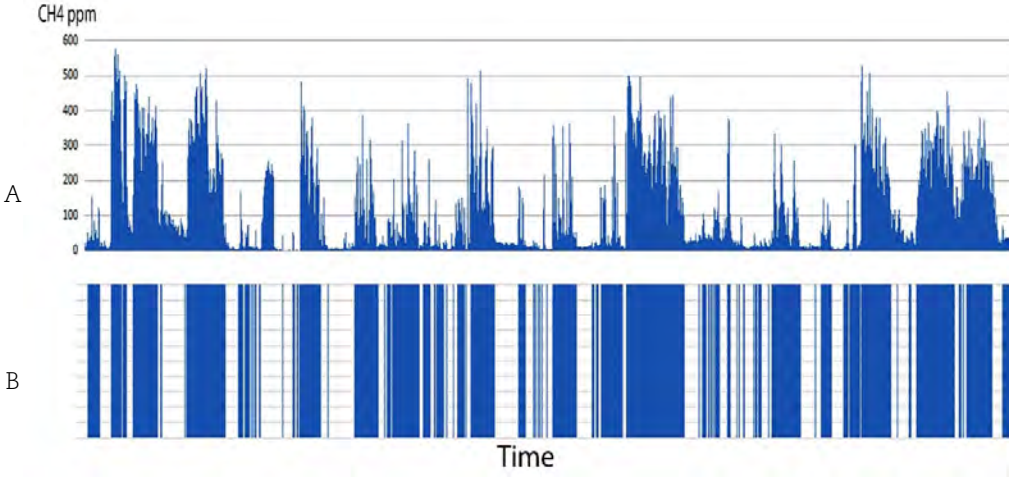

Figure 3. (A) CH_4 concentration (ppm) in ruminant's breath, and (B) Intake behavior across time

There is significant uncertainty associated with enteric CH_4 measurement techniques. Analysis of the database of the GLOBAL NETWORK project (Hristov *et al.*, 2018) showed that the coefficient of variation for CH_4 emission rate averaged 30, 28, and 18% for respiration chambers, SF6 and GreenFeed technique, respectively. Respiration chambers have been considered as the most accurate methodology to measure CH_4 emissions. But as Hristov *et al.* (2018) have pointed, even this method has critical sources of measurement variation (e.g. airflow rate through the chamber and the dynamics of air mixing in the chamber). Additionally, respiration chambers potentially inhibit animal behaviour and affect feed intake, especially when animals from grazing systems are driven and enclosed in these chambers.

Even if the limitations pointed by Berends *et al.* (2014) in the SF6 technique (e.g. the proportions of exhaled and eructated air in the air samples collected, or the distance of sampling point) are overcome, probably the SF6 technique will not be adequate to estimate enteric CH_4 emissions in the near future because of the high SF6 Global Warming Potential (24,000 CO^2-eq) and its long life in the atmosphere (over 3,000 years). In the GreenFeed technique, the number and timing of animal's visits to the unit are the most relevant sources of error, because these variables depend on the type of animal, the diet fed, and the level of dry matter intake (Hammond *et al.*, 2016).

In comparison with respiration chambers, our device cannot measure the total enteric CH_4 emissions. But our device could be used to find a mathematical relationship between changes in CH_4 concentration in ruminant's breath and CH_4 emissions, in a similar way to accepted methods (i.e. SF6 and GreenFeed). Taking into account the device usage in grazing animals, the SF6 technique could be used to find this mathematical relationship. Given that factors such as wind speed, the proximity of other animals, rain, and other environmental factors are not considered in respiration chambers.

On the other hand, the qualitative relationship between intake dynamics and CH_4 emissions established by our device is a relevant fact, because it probably means that alternative variables (e.g. Intake time) can be used in GHG inventories. The relationship between intake dynamic and enteric CH_4 emissions (Crompton *et al.,* 2011) and between intake time and enteric CH_4 emissions (Munoz-Tamayo *et al.,* 2018) have been previously established. In line with Munoz-Tamayo *et al.* (2018), who suggest that intake time is a good predictor to estimate enteric CH_4 emissions, and given the increasing usage of accelerometers in livestock, probably the intake dynamic recorded by accelerometers can be a method to estimate CH_4 emissions in on-farm conditions and from a large number of animals.

Conclusions

Our device can be a useful tool for studying the daily pattern of CH_4 emissions and feeding behaviour in ruminants. The feeding activity, measured by accelerometers, can be used to estimate enteric CH_4 emissions in grazing ruminants. However, further research is necessary to develop equations which include variables as live weight, milk yield or feed digestibility.

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References

Berends, H., Gerrits, W.J.J., France, J., Ellis, J.L., Van Zijderveld, S.M., & Dijkstra, J. (2014). Evaluation of the SF6 tracer technique for estimating methane emission rates with reference to dairy cows using a mechanistic model. *Journal of theoretical biology*, 353: 1–8.

Chagunda, M.G.G., & Yan, T. (2011). Do CH4 measurements from a laser detector and an indirect open-circuit respiration calorimetric chamber agree sufficiently closely?. *Animal Feed Science and Technology*, 165(1-2): 8–14.

Crompton, L.A., Mills, J.A., Reynolds, C.K., & France, J. (2011). Fluctuations in methane emission in response to feeding pattern in lactating dairy cows. *In Modeling nutrient digestion and utilization in farm animals* (pp. 176-180). Wageningen Academic Publishers, Wageningen.

Hammond, K.J., Crompton, L.A., Bannink, A., Dijkstra, J., Yáñez-Ruiz, D.R., O'Kiely, P., ... & Schwarm, A. (2016). Review of current in vivo measurement techniques for quantifying enteric methane emission from ruminants. *Animal feed science and technology*, 219: 13–30.

Hellwing, A.L.F., Weisbjerg, M.R., Brask, M., Alstrup, L., Johansen, M., Hymøller, L., ... & Lund, P. (2016). Prediction of the CH4 conversion factor (Ym) for dairy cows on the basis of national farm data. *Animal Production Science*, 56(3): 535–540.

Hristov, A.N., Kebreab, E., Niu, M., Oh, J., Bannink, A., Bayat, A.R., ... & Dijkstra, J. (2018). Symposium review: Uncertainties in enteric methane inventories, measurement techniques, and prediction models. *Journal of Dairy Science*, 101(7): 6655–6674.

Johnson KA, Westberg HH, Michal JJ, Cossalman MW (2007). The SF6 tracer technique: CH4 measurement from ruminants. *In 'Measuring CH4 production from ruminants'*. (Eds HPS Makkar, PE Vercoe) pp. 33–67. (Springer: Dordrecht, The Netherlands).

Knapp, J.R., Laur, G.L., Vadas, P.A., Weiss, W.P., & Tricarico, J.M. (2014). Invited review: Enteric methane in dairy cattle production: Quantifying the opportunities and impact of reducing emissions. *Journal of Dairy Science*, 97(6): 3231–3261.

La Notte, A., Tonin, S., & Lucaroni, G. (2018). Assessing direct and indirect emissions of greenhouse gases in road transportation, taking into account the role of uncertainty in the emissions inventory. *Environmental Impact Assessment Review*, 69: 82–93.

Madsen, J., B.S. Bjerg, T. Hvelplund, M.R. Weisbjerg, and P. Lund. (2010). Methane and carbon dioxide ratio in excreted air for quantification of the methane production from ruminants. *Livest. Sci.*, 129: 223–227.

Mattachini, Gabriele *et al.* Monitoring feeding behaviour of dairy cows using accelerometers. *Journal of Agricultural Engineering*, 2016, 47(1): 54–58.

Munoz-Tamayo, R., Agudelo, J.R., Dewhurst, R.J., Miller, G., Vernon, T., & Kettle, H. (2018). A parsimonious software sensor for estimating the individual dynamic pattern of methane emissions from cattle. *Animal*, 1–8.

Noguera, R.R., & Posada, S.L. (2017). Factor de emisión de metano entérico para vacas Holstein lactantes en la zona norte de Antioquia-Colombia. *Livestock Research for Rural Development*, 29, 6.

Prince, P.G.K., Hemamalini, R., & Rajkumar, R.I. (2014). LabVIEW based abnormal muscular movement and fall detection using MEMS Accelerometer during the occurrence of seizure. Indian Journal of Science and Technology, 7(10): 1625–1631.

Vinaya, C.H., Thanikanti, V.K., & Ramasamy, S. (2017). Environment quality monitoring using ARM processor. *In IOP Conference Series: Materials Science and Engineering* (Vol. 263, No. 5, p. 052020). IOP Publishing.

Waghorn, G. (2014). Technical Manual on Respiration Chamber Designs.

Zimmerman PR, Zimmerman RS (2012). Method and system for monitoring and reducing ruminant CH4 production. United States Patent number US20090288606A.

Appendix 1. Device code

```
#include <TimeLib.h>
#include "MPU6050.h"
#include <SD.h>


const int chipSelect = 10;
MPU6050 accelgyro;
int16_t ax, ay, az;
int16_t gx, gy, gz;

void setup() {
Serial.begin (9600);
setTime (00,00,00,00,00,0000);
pinMode (chipSelect,OUTPUT);
if (!SD.begin (chipSelect)){
Serial.print ("SD card error");
return;
}

File dafile = SD.open ("Sensor.txt", FILE_WRITE); // Create a txt file
String dataString = "";
dataString += String ("Time  CH4_ppm ax  ay  az  gx  gy  gz"); // Variables order in txt file
if (dafile){
dafile.println (dataString);
dafile.close();
Serial.println (dataString);
}

else{
Serial.println ("ERROR");
}
accelgyro.initialize();
}

// storing data in SD card
void loop() {
// Read raw accel/gyro data
accelgyro.getMotion6 (&ax, &ay, &az, &gx, &gy, &gz);
String dataString = "";
time_t t = now();
dataString += String(hour(t));
dataString += String(":");
dataString += String(minute(t));
dataString += String(":");
dataString += String(second(t));
dataString += " ";
// Read MQ4
dataString += String (analogRead(A0));
dataString += " ";
// Read Accelerometer
dataString += String(ax);
dataString += " ";
dataString += String(ay);
dataString += " ";
dataString += String(az);
dataString += " ";
dataString += String(gx);
dataString += " ";
dataString += String(gy);
dataString += " ";
dataString += String(gz);
dataString += " ";

File dafile = SD.open("Sensor.txt", FILE_WRITE); // Open txt file
if (dafile){
dafile.println(dataString);
dafile.close();
Serial.println(dataString);
}

else{
Serial.println("ERROR");
}
delay(1000); // Time interval
}
```

Development and implementation of machine vision techniques to measure eye temperature, heart rate and respiratory rate in dairy cattle

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Abstract

The aim of this study was to develop and implement machine vision techniques to measure heart rate (HR), respiratory rate (RR), and eye temperature in cattle. The sensors used in this study were thermal infrared cameras and RGB video cameras, with the aim of simultaneously recording thermal and RGB (Red, Green and Blue) images of the cows face while each cow was individually confined in a crush. Suitable images were manually selected and subsequently processed using customised algorithms. This research compared the vaginal temperature, heart rate and respiration rate obtained from conventional methods (intravaginal loggers, heart rate Polar monitor and visual observations respectively) with the eye temperature, heart rate and respiration rate obtained from the non-invasive techniques (thermal images, RGB videos and Infrared videos respectively). The results of this study showed high correlations between the data obtained from conventional methods and the data obtained from these non-invasive methods. The correlations between the vaginal temperature obtained from the vaginal loggers and the eye temperature obtained from thermal images, between the heart rates from the Polar monitor and the analysis of RGB videos, and between the respiration rate from visual observations and the image processing ranged between $r = 0.78$ and $r = 0.88$. These results suggest that machine vision techniques could be useful non-invasive methods able to assess changes in physiological parameters, such as HR, RR and skin temperature in cattle.

Keywords: remote-sensing, animal monitoring, physiological changes, imagery

Introduction

As livestock farming becomes more intensive, more sustainable systems and new technologies are required to improve animal management (Tullo *et al.*, 2018). Therefore, Precision Livestock Farming (PLF) can contribute to improving animal management and production (Berckmans, 2014; Van Hertem *et al.*, 2016). For instance, the robotic-milking system (RMS) has been one of the new technologies that has assisted in the improvement of management and productivity in dairy farms (Hyde & Engel, 2002). This system not only allows the voluntary approach of cows to the milking robot, but also allows the monitoring of parameters such as frequency of milking, amount of milk produced and food intake, to name a few (Jacobs & Siegford, 2012). Also, as part of the growth in PLF, sound and optical sensors have started to be researched and implemented in order to develop new technologies able to assist in animal monitoring (Van Hertem *et al.*, 2016).

Optical sensors and machine vision (MV) techniques are increasingly being used in research related to human and animal monitoring (Tscharke & Banhazi, 2016). For example, Guo *et al.* (2015) and Wang *et al.* (2008) implemented MV techniques to monitor animal behaviour. Moreover, other studies have used this technology to identify health problems such as foot disease (Poursaberi *et al.*, 2010).

As MV techniques have shown to be useful tools to remotely monitor animal and humans, several researchers have studied image-based techniques which can measure physiological parameters, which can be used to indicate health, emotions and wellbeing assessment

(Gómez *et al.*, 2018; Wu *et al.*, 2012).The aim is to reduce the need for contact techniques for the assessment of physiological changes (Lee *et al.*, 2018). For instance, thermal imaging has widely been studied to measure skin temperature in humans and animals. In the case of cattle and other animals, this technology has been implemented to measure eye temperature, as an indicator of core body temperature (George *et al.*, 2014). Researchers such as Schaefer *et al.* (2007) and Unruh *et al.* (2017) have shown the promising capability of thermal-imaging techniques to detect temperature changes in animals, which could assist animal monitoring on farms.

Scientists and producers have also put effort into developing contactless techniques able to measure parameters such as heart rate (HR) and respiration rate (RR), in order to avoid the contact needed by the most commonly used methods (e.g. stethoscope). In this matter, MV techniques have been used in studies relating to humans, which lead to the investigations aimed at remotely measuring HR and RR in animals (Jukan *et al.*, 2017; Zhao *et al.*, 2013). HR measured through MV techniques has mainly been studied in humans by researchers such as Poh *et al.* (2010) and Balakrishnan *et al.* (2013), who analysed videos of people's faces, obtained with commercial RGB (red, green and blue) cameras, in order to detect heart beats and determine HR of people. In addition, some scientists who developed algorithms for detecting HR in humans attempted to apply them to animals. However, animals need to be anesthetized during the recording (Barbosa Pereira *et al.*, 2018). This indicates the opportunity for further research relating to the development and implementation of MV techniques that are able to measure HR of animals on a farm in a less invasive manner.

Similarly, some research has focused on the use of MV technology to determine RR. For example, Stewart *et al.* (2017) showed positive results when using infrared thermography to detect RR in dairy cows. However, their method required observation of the images and manually counting of the air movements, which is impractical for large scale monitoring.

This pilot study aimed to identify the potential for the proposed MV techniques to remotely measure eye temperature, HR and RR in dairy cows.

Material and methods

Data acquisition

The protocol of this study was approved by The University of Melbourne's Animal Ethics Committee. This experiment was conducted on a robotic dairy farm, where ten cows were randomly selected from the herd. The participating cows were separated from the group the night before and kept in a holding yard overnight during the days of the study. The experiment was conducted over three consecutive days, during the morning.

Each parameter included in the study was measured with two methods; one conventional and one video-computer-based method. Body temperature was measured by vaginal temperature loggers (Thermochron® attached to a CIDR), which were placed in each cow the night before the experiment started and were removed the third day after the experiment finished. The optical sensors used in this study were a thermal camera (FLIR AX8 Thermal Imaging Camera) and an RGB video camera (Raspberry Pi Cameras Module V2). Eye temperature was analysed from the thermal images obtained. HR was obtained by a heart rate monitor (Polar WearLink®), fitted to the animals during the time of the experiment, and by the processing of the RGB videos obtained. Finally, the RR of cows was determined by visual observation from video recordings and by the analysis of infrared images.

As part of the procedure, animals were individually placed in the crush two times each morning (once before their morning milking and then again immediately after the

milking). When the cow was in the crush for first time, the heart rate monitor was fitted on the thorax with an elastic band. After this procedure, the animal's head was captured with the head bail of the crush in order to record videos and images of the face during three minutes. During this recording, a technician held the cameras in front of the cow's face, at a distance of 1.5 metres. As soon as the recording was finished, the crush was opened and the cow was allowed to go to the milking robot. After the milking, the cow was again drafted to the crush, its head was positioned in a similar manner to the first time, and the face was recorded for an additional three minutes. After this period, the heart rate monitor was removed and the animals were released, allowing them to return to pasture with the herd during the afternoon.

Data analysis

Infrared (IR) images (radiometric and non-radiometric) and RGB videos were processed with customised algorithms written in Matlab® R2016a (Mathworks Inc. Matick, MA, USA). For eye temperature, the eye area was manually selected as the region of interest (ROI), from which the temperature was extracted for each image. In the case of RGB videos, each recording was reviewed, divided into 30 second videos, and the 30 second video with better quality was selected to be processed. For this analysis, the eye area was manually selected as ROI and this was then processed with the customized algorithm, which determines HR from the changes of luminosity detected within the ROI. Finally, non-radiometric IR videos were processed using a customized algorithm to measure RR. The first step for this analysis was to evaluate the collected footage and select the videos that presented the slightest motion. After that, the ROI (nose) was selected on the footage and processed to determine RR from the change in pixel intensity values within the ROI.

After the data was obtained from the image processing, this data was compared with the data obtained from temperature loggers, HR Polar monitors and visual observations respectively. Correlation was analysed between temperature obtained from thermal images and temperature loggers, between HR obtained from RGB videos and HR monitors, and between RR obtained from non-radiometric videos and visual observations. This analysis was performed in SAS® 9.4.

Results and discussion

In order to identify the accuracy of the proposed technique in measuring eye temperature as an index of core body temperature, the data obtained from this technique were compared with the vaginal temperature obtained from the logger during the same time-period. The eye temperature obtained from the thermal images ranged from 34.5–37.4 °C, showing a similar range to the eye temperature previously observed in cattle (Gómez *et al.*, 2018). The vaginal temperature ranged between 38.2–39.2 °C, similar to the values obtained by Suthar *et al.* (2013) when measuring vaginal temperature with temperature loggers in cattle. As shown in Table 1, the correlation coefficient (*r*) was calculated in order to compare both methods.

Table 1. Pearson correlation coefficients (*r*) between measurements acquired from conventional and proposed techniques

Physiological parameter	Correlation between methods (r)	p-Value
Temperature	0.88	$P < 0.001$
Heart rate	0.81	$P < 0.001$
Respiration rate	0.77	$P < 0.001$

In order to evaluate the performance of the proposed MV technique for HR measurement, the data collected by this technique were compared to the data obtained using the HR monitor. As Figure 1 shows, the set of data was obtained through Polar® ProTrainer 5™ software and Matlab® R2016a respectively, and the two periods when cows were recorded in the crush were identified. The values of BPM (beats per minute) of the same time-period were extracted and a correlation test was performed. This analysis showed a positive correlation between the BPM obtained using both methods (Table 1). These results are similar to what was observed by Poh *et al.* (2010), who obtained a $r = 0.89$ when comparing the output of HR in people from webcam videos and a finger blood volume pulse (BVP) sensor.

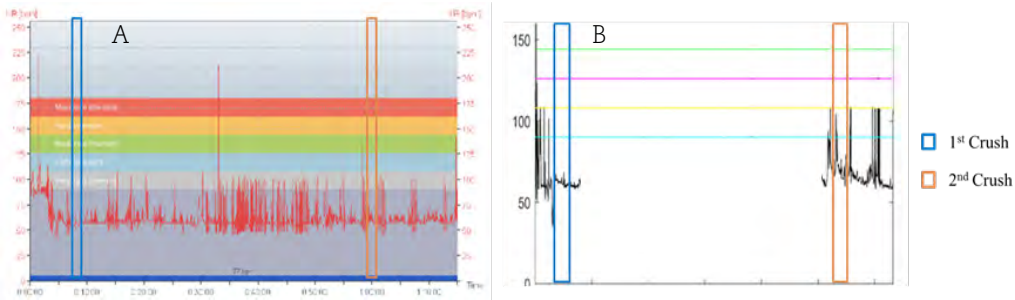

Figure 1. Example of HR output from (A) HR POLAR monitors and (B) RGB video recording, where it is possible to observe the two periods of recording when the animal was in the crush

Similarly, RR was evaluated by the visual observation process and by the image processing, followed by the comparison between both outputs. Table 1 shows that there was a moderate correlation between these two methods, with $r = 0.77$ ($P < 0.001$). The results obtained for this and the other parameters were promising, however, the motion of cows and / or cameras made the selection of images more laborious and resulted in some noise that needs to be considered. These observations have led to further research in order to improve the practicability and accuracy of the method for the analysis of these parameters.

Conclusions

This pilot study examined machine vision techniques to remotely assess eye temperature, HR and RR in dairy cattle. Based on good correlations with physical measures, these methods could potentially be used in practical applications in the livestock industries through measuring physiological parameters and improving the assessment of emotional and physical state of farm animals. However, manually selection of images is a limitation for practical use, indicating the need for research that aims to increase the accuracy and automatization of the proposed techniques.

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References

Balakrishnan, G., Durand, F., & Guttag, J. (2013). *Detecting pulse from head motions in video.* Paper presented at the Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition.

Barbosa Pereira, C., Kunczik, J., Zieglowski, L., Tolba, R., Abdelrahman, A., Zechner, D., . . . Czaplik, M. (2018). Remote Welfare Monitoring of Rodents Using Thermal Imaging. *Sensors,* 18(11): 3653.

Berckmans, D. (2014). Precision livestock farming technologies for welfare management in intensive livestock systems. *Scientific and Technical Review of the Office International des Epizooties,* 33(1): 189–196.

George, W., Godfrey, R., Ketring, R., Vinson, M., & Willard, S. (2014). Relationship among eye and muzzle temperatures measured using digital infrared thermal imaging and vaginal and rectal temperatures in hair sheep and cattle. *Journal of Animal Science,* 92(11): 4949–4955.

Gómez, Y., Bieler, R., Hankele, A.K., Zähner, M., Savary, P., & Hillmann, E. (2018). Evaluation of visible eye white and maximum eye temperature as non-invasive indicators of stress in dairy cows. *Applied Animal Behaviour Science,* 198: 1–8.

Guo, Y.-z., Zhu, W.-x., Jiao, P.-p., Ma, C.-h., & Yang, J.-j. (2015). Multi-object extraction from topview group-housed pig images based on adaptive partitioning and multilevel thresholding segmentation. *Biosystems Engineering,* 135: 54–60.

Hyde, J., & Engel, P. (2002). Investing in a robotic milking system: A Monte Carlo simulation analysis. *Journal of Dairy Science,* 85(9): 2207–2214.

Jacobs, J., & Siegford, J. (2012). Invited review: The impact of automatic milking systems on dairy cow management, behavior, health, and welfare. *Journal of Dairy Science,* 95(5): 2227–2247.

Jukan, A., Masip-Bruin, X., & Amla, N. (2017). Smart computing and sensing technologies for animal welfare: a systematic review. *ACM Computing Surveys (CSUR)* 50(1), 10.

Lee, C., Colditz, I.G., & Campbell, D.L. (2018). A framework to assess the impact of new animal management technologies on welfare: a case study of virtual fencing. *Frontiers in Veterinary Science,* 5.

Poh, M.-Z., McDuff, D.J., & Picard, R.W. (2010). Non-contact, automated cardiac pulse measurements using video imaging and blind source separation. *Optics express,* 18(10): 10762–10774.

Poursaberi, A., Bahr, C., Pluk, A., Van Nuffel, A., & Berckmans, D. (2010). Real-time automatic lameness detection based on back posture extraction in dairy cattle: Shape analysis of cow with image processing techniques. *Computers and Electronics in Agriculture,* 74(1): 110–119.

Schaefer, A., Cook, N., Church, J., Basarab, J., Perry, B., Miller, C., & Tong, A. (2007). The use of infrared thermography as an early indicator of bovine respiratory disease complex in calves. *Research in Veterinary Science,* 83(3): 376–384.

Stewart, M., Wilson, M., Schaefer, A., Huddart, F., & Sutherland, M. (2017). The use of infrared thermography and accelerometers for remote monitoring of dairy cow health and welfare. *Journal of Dairy Science,* 100(5): 3893–3901.

Suthar, V., Burfeind, O., Maeder, B., & Heuwieser, W. (2013). Agreement between rectal and vaginal temperature measured with temperature loggers in dairy cows. *Journal of Dairy Research,* 80(2): 240–245.

Tscharke, M., & Banhazi, T.M. (2016). A brief review of the application of machine vision in livestock behaviour analysis. *Agrárinformatika/Journal of Agricultural Informatics,* 7(1): 23–42.

Tullo, E., Finzi, A., & Guarino, M. (2018). Environmental impact of livestock farming and Precision Livestock Farming as a mitigation strategy. *Science of The Total Environment*.

Unruh, E.M., Theurer, M.E., White, B.J., Larson, R.L., Drouillard, J.S., & Schrag, N. (2017). Evaluation of infrared thermography as a diagnostic tool to predict heat stress events in feedlot cattle. *American Journal of Veterinary Research,* 78(7): 771–777.

Van Hertem, T., Lague, S., Rooijakkers, L., & Vranken, E. (2016). Towards a sustainable meat production with precision livestock farming. *Proceedings in Food System Dynamics,* 357–362.

Wang, Y., Yang, W., Winter, P., & Walker, L. (2008). Walk-through weighing of pigs using machine vision and an artificial neural network. *Biosystems Engineering,* 100(1): 117–125.

Wu, H.-Y., Rubinstein, M., Shih, E., Guttag, J., Durand, F., & Freeman, W. (2012). Eulerian video magnification for revealing subtle changes in the world. *ACM Transactions on Graphics,* 31(4): 1–8.

Zhao, F., Li, M., Qian, Y., & Tsien, J.Z. (2013). Remote measurements of heart and respiration rates for telemedicine. *PloS one,* 8(10): e71384.

Considering pre-processing of accelerometer signal recorded with sensor fixed on dairy cows is a way to improve the classification of behaviours

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Abstract

Health events can be detected by monitoring the behaviour of dairy cows with an accelerometer. To our knowledge, there is no study on the steps preceding the classification, namely accelerometer signal pre-processing in dairy cows. Using accelerometer data, the present study aimed to (i) evaluate the impact of the most commonly used pre-processing methods on the performance of predictions achieved with a classifier and (ii) evaluate whether this impact is related to changes in the relative importance of features used by the classifier. Ten dairy cows were equipped with a three-dimensional accelerometer fixed on a collar and were observed simultaneously. Several methods of pre-processing were combined, including different filters (high-pass filter and low-pass filter), window sizes and overlapping percentages. A decision tree was applied to classify the behaviours. The F-score was computed for each combination and an analysis of variance was applied to compare each effect. The relative importance of features was evaluated using the Gini index provided with the random forest algorithm output. The F-score decreased significantly ($P < 0.001$) when a high-pass filter was applied and the relative importance of features was modified, suggesting that the continuous component is essential for the classification. The increase of window size and percentage of overlap improved the classification ($P < 0.001$) but it was not explained by a change in the relative importance of features. No impact was found for the low-pass filter and normalization. Finally, the optimal setting includes no high-pass filter, a window size of 20 s and 30 s, and an overlap of 90%.

Keywords: Accelerometer signal pre-processing, dairy cow, behaviour classification, relative feature importance

Introduction

Monitoring livestock behaviour can be a useful way to detect health events (Chapinal *et al.*, 2009). However, observation of animals is time consuming and labour-intensive. For these reasons, accelerometers that automatically monitor the behaviour of livestock can be a good solution (Rushen *et al.*, 2012). The critical point for the development of sensors for their use on farm is the accurate prediction of specific animal behaviours from raw acceleration data.

Two main steps are usually undertaken to predict behaviours from raw data acceleration (Brown *et al.*, 2013): first the raw data are pre-processed (**pre-processing step**) and then the pre-processed data are used as input for a prediction algorithm (**classification step**). The step of the pre-processing consists of processing the raw accelerometer data to get a suitable dataset for the prediction algorithm. Signal is filtered at first to remove the noise and possibly to discard the static component of the acceleration. Then, signal is segmented into different windows of the same size with or without overlap. Features are extracted to summarise the signal windows. These features can then be normalized in order to reduce the variability between individuals.

Once the data have been pre-processed, the classification step is applied to predict behaviours by applying an appropriate classifier on the extracted features. The performance of the prediction is evaluated by comparing observed and predicted behaviours.

Most of the previous studies on the prediction of livestock behaviour from sensor data have focused on the classifier rather than on the pre-processing. Several authors have compared the performance of different datamining methods to discriminate behaviours, with some methods appearing clearly more effective than others (Nathan *et al.*, 2012).

Different pre-processing methods have been used in livestock behaviour monitoring but their impact on the prediction of behaviours has never been evaluated, except for the comparison of different window sizes (Vázquez Diosdado *et al.*, 2015; Smith *et al.*, 2016). However, in other classification problem based on accelerometer data, such as in human activity recognition, the impact of pre-processing on the classification step has already been shown (Bersch *et al.*, 2014). Pre-processing could also impact the predictive ability of some extracted features, partially explaining the difference in predictive performance.

The aims of this study were to evaluate the effect of commonly used pre-processing methods on the performance of accelerometer data for the prediction of cattle behaviour and to quantify the relative importance of the features used by the classifier in the prediction. To this end, different parameters for the following pre-processing steps were investigated: filtering (low-pass filter and high-pass filter), window sizes, percentage of overlapping between windows and feature normalization (yes/no). All possible combinations of pre-processing steps were carried out and decision trees were used to predict observed cow behaviours. The F-score metric was computed to compare the performance. The Gini indexes returned by the random forest algorithm were used to compare the relative importance of the features between each pre-processing method.

Material and methods

Experimental data

The study was conducted in a 71 Holstein (milk yield: 10,000 kg per year) commercial farm based in Lion d'Angers (France) in July 2017. Cows were milked every day at 9 am and 6 pm and a supplement was distributed after each milking. The cows grazed day and night on temporary pasture, sown with a mixture of perennial ryegrass (*Lolium perenne L.*) and white clover (*Trifolium repens L.*). For the experiment, ten dairy cows ranging between 60–300 days in milk and representative of the herd in terms of parity were selected.

A RF-Track datalogger (RF-Track, Rennes, France) with a LSM9DS1, a three-axis accelerometer from STMicroelectronics, Geneva, Switzerland) was used. The dataloggers were 98.2 x 51.60 x 36.0 mm in size and weighed 250 g. Data were collected at 59.5 Hz. They were stored on a SD card and downloaded after the experiment.

Data collection

The three-axis accelerometer was fixed on a collar and positioned on the right side of the neck. A 500 g counterweight was added to prevent them from turning around. Collars were tightly adjusted. The x-axis detected the down-up direction, the y-axis detected the left-right direction and the z-axis detected the backward-forward direction. The ten cows were fitted with this collar during grazing from 11 am to 5 pm.

Cow behaviours were also recorded by two observers simultaneously. Observers tracked each equipped animal in turn continuously during 15 minute periods. This resulted in five hours of observations available for the 10 cows. The four behaviours recorded were "Grazing", "Walking", "Lying" and "Standing". All other observed behaviours were classified

as "Other". After data collection, accelerometers and observations were time synchronized to ensure that the sequences of accelerometer signal were correctly associated with the respective observed behaviours.

Data pre-processing

All the pre-processing steps were performed in Matlab R2017a software. Pre-processing was applied on the three axis of the 3D-accelerometer and on the magnitude of the signal, considered as orientation independent.

Several levels of filtering, segmentation and feature normalization were investigated. For the filtering, a low-pass filter with 5 Hz and 10 Hz cut-off frequencies were applied to evaluate the impact of the reduction in signal noise (Lee and Kwan, 2018). A z high-pass filter with 0.3 Hz cut-off frequency was sometimes used to remove the static component of the acceleration (Benaissa *et al.*, 2018). A segmentation was considered for different window sizes (3 s, 5 s, 10 s, 20 s and 30 s) and for percentages of overlap between consecutive windows (0%, 25%, 50%, 75% and 90%). The same 61 features were then extracted from the segmented signal, including position parameters such as mean and median. Dispersion parameters such as variance, standard deviation, minimum, maximum and interquartile range were also calculated. Other features commonly used were also extracted, including the Signal Magnitude Area (Barwick *et al.*, 2018) and the Movement Variation (Barwick *et al.*, 2018). Spectral entropy was extracted from the frequency domain (Zaccarelli *et al.*, 2013). Lastly, a normalization step was either applied or not on these features. As a result, 300 different datasets representing 300 combinations of pre-processing steps were obtained.

Data processing

The study of the relative importance of the features and the classification step were both performed with R 3.4.0 software (R Core Team, 2017). A decision tree using the 61 extracted features from each pre-processed configuration as inputs was used to predict the observed behaviours with the rpart package (Therneau & Atkinson, 2018). For each combination, the random forest algorithm was applied with the randomForest package (Liaw & Wiener, 2002). Once the random forest algorithm had been calibrated for each pre-processing combination, the relative importance of each feature was estimated by the mean decrease in the Gini index. The higher the mean decrease in the Gini index, the more the feature was important in the prediction of cow behaviours.

Evaluation of the impact of the pre-processing steps

A 10-fold cross-validation procedure was applied to evaluate the performance of each of the 300 models obtained with decision trees. The confusion matrix was obtained at the end on the procedure and the F-score metric was computed based on this confusion matrix. The F-score metric is the harmonic mean of precision and recall, ranging between 0–1. The better the model is performing, the closer the F-score will be to 1. The relation between indicators of predictive performance and pre-processing parameters was evaluated using linear models, leading to the following initial model:

$$Fscore \sim \alpha + \beta_1 HPF + \beta_2 LPF + \beta_3 WS + \beta_4 POV + \beta_5 NORM + \beta_6 WS{:}POV + \varepsilon \qquad (1)$$

where the outcome was the *F-score*. High-pass filter (*HPF*), low-pass filter (*LPF*), window size (*WS*), percentage overlap (*POV*), normalization (*NORM*) and the interaction between window size and percentage of overlap (*WS : POV*) were the explanatory variables. Finally α was the overall mean, $\beta_1, \ldots, \beta_5$ were the coefficients to estimate and ε was the residual error. A backward procedure was adopted to get the final model with only significant parameters. ANOVA of type III was carried out with car package (Fox & Weisberg, 2011) in R. A Tukey test was finally applied on each explicative parameter to identify the levels

which were significantly different from each other. The Tukey test was carried out in R, with the lsmeans package (Lenth, 2016).

For each parameter of pre-processing, the mean decrease in Gini index associated with each feature was expressed as a percentage of the total mean decrease in Gini index for the corresponding parameter level. A heatmap was plotted for each parameter to quickly determine whether the relative importance of each feature depended on the chosen level for the parameter.

Results and discussion

The impact of each pre-processing step on the prediction of cow behaviours and on the relative importance of features were explained in each following section. Results from the ANOVA for each parameter are presented in Table. 1.

Impact of filtering

No significant effect was found for the low-pass filter (Table 1), suggesting that removing signal noise did not improve the prediction in this study. The relative importance of features was not influenced by the chosen level for the low-pass filter (data not shown).

The F-score was decreased by the use of a high-pass filter (- 0.06; $P < 0.001$; Table 1), which is in agreement with Erdaş *et al.* (2016). Furthermore, the relative importance of features was strongly affected by the use of the high-pass filter (Figure 1). High-pass filtering at 0.3 Hz cut-off frequency removes the continuous component of each axis, which is similar to substract the average value from the raw signal. Position parameters like the mean are greatly affected by the high-pass filtering and become irrelevant for the classification step, in particular the mean on the y-axis (Figure 1: "mean_accy"). Simultaneously, the relative importance of features which were not affected by the filter, like variations of movement (Figure 1: "MV_accx", "MV_accy", "MV_accz" and "MV"), were increased. Based on the prediction results (Table 1.), this suggests that the static component of the acceleration is essential to discriminate cow behaviours.

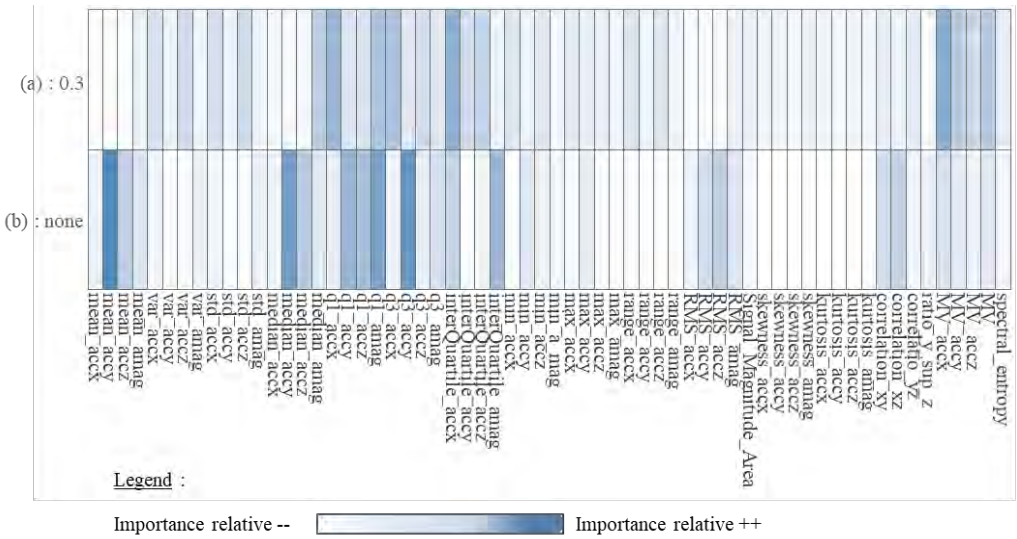

Figure 1. Relative importance of features in the classification procedure of cow behavious by the random forest algorithm, with a high-pass filter at 0.3 Hz cut-off frequency (a) and without high-pass filter (b)

Table 1. ANOVA results: evaluation of the pre-processing effect on the F-score

			F-score
	Effect	**Significance levels[1]**	**mean ± sd**
LPF	None	0.39	0.87[a] ± 0.06
	10 Hz		0.87[a] ± 0.07
	5 Hz		0.87[a]± 0.07
HPF	None	***	0.93[b] ± 0.05
	0.3 Hz		0.82[a] ± 0.02
WS	3	***	0.84[a] ± 0.08
	5		0.86[b] ± 0.07
	10		0.88[c] ± 0.06
	20		0.90[d] ± 0.05
	30		0.90[d] ± 0.04
POV	0	***	0.86[a] ± 0.07
	25		0.86[b] ± 0.06
	50		0.87[b] ± 0.06
	75		0.88[c] ± 0.07
	90		0.89[c] ± 0.07
NORM	None	0.45	0.87[a] ± 0.07
	With		0.87[a] ± 0.07
WS x POV		***	
adjusted R^2			0.88

Significant levels: *** P <0.001; ** P <0.01; * P <0.05; † P <0.1
[1] Effects of high-pass filter (HPF), low-pass filter (LPF), window size (WS), percentage of overlapping (POV), normalization (NORM), window size*percentage of overlapping (WS x POV)
[a - d] distinguish adjusted means that are different for high-pass filter, low-pass filter, window size, percentage of overlapping and normalization ($P < 0.05$, Tukey's pairwise comparison)

Impact of segmentation

The F-score increased with the window size until a threshold of 20 s ($P < 0.001$; Table 1) and was significantly lower when the window size of 3 s (- 0.04; $P < 0.001$; Table 1) and 5 s were applied (- 0.02; $P < 0.001$; Table 1). The window sizes of 20 s and 30 s led to a higher F-score (respectively: + 0.02; $P < 0.001$; Table 1 and + 0.03; $P < 0.001$; Table 1), as already shown in similar studies (Smith *et al.*, 2016). The relative importance of features was not influenced by the size of the window (data not shown). Wide windows are certainly more representative of the signal sequences than the short windows, explaining why the F-score are better (Vázquez Diosdado *et al.*, 2015).

Concerning overlapping, the F-score was also improved with the percentage of overlap until 75% ($P < 0.001$; Table 1). The F-score was decreased with the percentages of 0% (- 0.015; $P < 0.001$; Table 1) and 25% (- 0.012; $P < 0.001$; Table 1). Percentages of 75% and 90% led to the higher F-score (respectively: + 0.01; $P < 0.001$; Table 1 and + 0.02; $P < 0.001$; Table 1), in agreement with Bersch *et al.* (2014). The relative importance of features was

not affected by overlapping. The more the percentage of overlap increased, the more the number of signal windows used by the decision tree rose. This is probably why the results are better with high percentages of overlap.

Impact of normalization

Normalizing data was not associated with changes in F-score. The relative importance of features was also the same for each level of the low-pass filter.

The importance to consider the whole combination of the pre-processing steps

Two out of 300 combinations of pre-processing led to the best performance (F-score: 0.97). Both combinations included no high-pass filter, wide window size (20 s and 30 s), an overlap of 90% and feature normalization. Four combinations led to the lowest performance (F-score: 0.74). These combinations involved the low-pass filter at 5 Hz and 10 Hz, included the high-pass filter, the window size of 3 s with 0%, 25%, 50% and 75% percentages of overlap and with normalization. This result shows the importance of considering pre-processing step as a whole.

Conclusion

This study aimed to evaluate the effect of different approaches commonly used to pre-process three-dimensional accelerometer data on the prediction of the main behaviours of dairy cows. The impact of pre-processing steps on the relative importance of extracted features was also evaluated to better understand the prediction results. A decrease of performance was systematically observed when the high-pass filter was applied. The relative importance was also modified, as the high-pass filter directly impacts some features in removing the continuous component of the acceleration. This suggests that it is essential to keep this component for the prediction. The F-score was significantly improved with wide window sizes without changes in relative importance of features. The F-score was also increased with high overlaps without changes in the relative importance of features. Low-pass filter and normalization did not affect the classification in this study. The substantial difference obtained with the best and worst configurations of pre-processing shows the importance of considering each pre-processing step both separately as well as in combination. In particular, the best configurations were obtained without high-pass filter, with window sizes of 20 s and 30 s and with an overlap of 90%. Finally, features were extracted in this study without comparing the relevance of each of them in the classification process of each behaviour. Still focused on the impact of the pre-processing step, the evaluation of the prediction with different subsets of features deserves to be explored. It should be an interesting way to identify the best features to extract to optimise the prediction, depending on the considered behaviours.

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References

Barwick, J., Lamb, D.W., Dobos, R., Welch, M., Trotter, M. (2018). Categorising sheep activity using a tri-axial accelerometer. *Comput. Electron. Agric.*, 145: 289–297. https://doi.org/10.1016/j.compag.2018.01.007.

Benaissa, S., Tuyttens, F.A.M., Plets, D., Cattrysse, H., Martens, L., Vandaele, L., Joseph, W., Sonck, B. (2018). Classification of ingestive-related cow behaviours using RumiWatch halter and neck-mounted accelerometers. *Appl. Anim. Behav. Sci.* (in press).

Bersch, S., Azzi, D., Khusainov, R., Achumba, I., Ries, J. (2014). Sensor Data Acquisition and Processing Parameters for Human Activity Classification. *Sensors*, 14: 4239–4270. https://doi.org/10.3390/s140304239.

Brown, D.D., Kays, R., Wikelski, M., Wilson, R., Klimley, A.P. (2013). Observing the unwatchable through acceleration logging of animal behavior. *Anim. Biotelemetry*, 1:20.

Chapinal, N., de Passillé, A.M., Weary, D.M., von Keyserlingk, A.G., Rushen, J. (2009). Using gait score, walking speed, and lying behavior to detect hoof lesions in dairy cows. *Journal of Dairy Science* 92, 4365–4374. https://doi.org/10.3168/jds.2009–2115.

Erdaş, Ç.B., Atasoy, I., Açıcı, K., Oğul, H. (2016). Integrating Features for Accelerometer-based Activity Recognition. *Procedia Comput. Sci.* 98: 522–527. https://doi.org/10.1016/j.procs.2016.09.070.

Fox, J. and Weisberg, S. (2011). An {R} Companion to Applied Regression, Second Edition. Thousand Oaks CA: Sage. URL: http://socserv.socsci.mcmaster.ca/jfox/Books/Companion.

Lee, K., Kwan, M.-P. (2018). Physical activity classification in free-living conditions using smartphone accelerometer data and exploration of predicted results. Comput. Environ. *Urban Syst.* 67, 124–131. https://doi.org/10.1016/j.compenvurbsys.2017.09.012.

Lenth, R.V. (2016). Least-Squares Means: The R Package lsmeans. *Journal of Statistical Software,* 69(1): 1–33. doi:10.18637/jss.v069.i01.

Liaw, A. and Wiener, M. (2002). Classification and Regression by randomForest. R News, 2(3): 18–22.

Nathan, R., Spiegel, O., Fortmann-Roe, S., Harel, R., Wikelski, M., Getz, W.M. (2012). Using tri-axial acceleration data to identify behavioral modes of free-ranging animals: general concepts and tools illustrated for griffon vultures. *J. Exp. Biol.*, 215: 986–996. https://doi.org/10.1242/jeb.058602.

Rushen, J., Chapinal, N., de Passillé, A. (2012). Automated monitoring of behavioural-based animal welfare indicators. *Anim. Welf.*, 21: 339–350. https://doi.org/10.7120/09627286.21.3.339.

Smith, D., Rahman, A., Bishop-Hurley, G.J., Hills, J., Shahriar, S., Henry, D., Rawnsley, R. (2016). Behavior classification of cows fitted with motion collars: Decomposing multi-class classification into a set of binary problems. *Comput. Electron. Agric.,* 131: 40–50. https://doi.org/10.1016/j.compag.2016.10.006.

Therneau, T. and Atkinson, B. (2018). rpart: Recursive Partitioning and Regression Tree. R package version 4.1-13 https://CRAN.R-project.org/package=rpart.

Vázquez Diosdado, J.A., Barker, Z.E., Hodges, H.R., Amory, J.R., Croft, D.P., Bell, N.J., Codling, E.A. (2015). Classification of behaviour in housed dairy cows using an accelerometer-based activity monitoring system. *Anim. Biotelemetry,* 3:15. https://doi.org/10.1186/s40317-015-0045–8.

Zaccarelli, N., Li, B.-L., Petrosillo, I., Zurlini, G. (2013). Order and disorder in ecological time-series: Introducing normalized spectral entropy. *Ecol. Indic.,* 28: 22–30. https://doi.org/10.1016/j.ecolind.2011.07.008.

Use of a 3D imaging device to model the complete shape of dairy cattle and measure new morphological phenotypes

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Abstract

Monitoring of body weight variation, body condition and/or morphological changes allows optimal management of animal health, production and reproduction performance. However, due to implementation difficulties (handling, time consumption, investments) this type of monitoring is not very common on commercial farms. The development of three-dimensional imaging technologies is an interesting solution to meet these needs. The purpose of this study was to develop, test and validate a device (Morpho3D) offering the possibility of recording and analysing complete 3D forms of dairy cattle. To evaluate the performance of this tool, manual measurements were performed on 30 Holstein dairy cows: wither height (WH), heart girth (HG), chest depth (CD), hip width (HW), thirl width (TW) and ischium width (IW). They were compared to those measured from the Morpho3D device. Correlations between Morpho3D measurements and manual measurements were 0.89 for CD, 0.80 for HW, 0.78 for HG, 0.76 for TW, 0.63 for IW and 0.62 for WH. For the Morpho3D system, the repeatability standard deviation ranged from 0.34–1.89 (coefficient of variation (CV) from 0.26–9.81) and the reproducibility standard deviation ranged from 0.55–5.87 (CV from 0.94–7.34). These values are close to those obtained with manual measurements. This new device offers the possibility of measuring new phenotypes such as the total volume of the animal or the body surface and thus offers new research opportunities.

Keywords: dairy cattle, 3D imaging, morphology

Introduction

Monitoring the evolution of the morphology of dairy cattle through the measurement of live weight (LW), morphological change (chest circumference, height at withers, etc.) or body condition score (BCS), allows to the adaptation of feeding, reproduction and general management for optimal operation of the farm. Currently, with the exception of weight, most measurements are done manually (tape, measuring rod) or visually (Heinrichs & Hardgrove, 1987). These measures are time-consuming, and are sources of stress and accidents for farmers and animals. As a result, and despite their value, this information is not available on the farm. Developing precise, automatic and easy-to-use tools to overcome these problems is therefore of interest. Imaging techniques offer interesting alternatives to manual measurements and/or costly methods (Pezzulo *et al.*, 2018). 2D imaging approaches, used in pork with some success (Marchant *et al.*, 1993, Schofield *et al.*, 1998), do not allow users to approach the third dimension. In addition, distortion problems, the calibration procedure, the need for multiple cameras and finally 3D reconstruction models have reduced their use. The development and commercialization of 3D cameras at a relatively low cost has reduced the interest in this 2D technology in favour of 3D cameras. These new imaging technologies have thus been used successfully to analyse the BCS of dairy cattle (Bercovich *et al.*, 2013, Fischer *et al.*, 2015, Kuzuhara *et al.*, 2015). Negretti *et al.* (2008), Buranakarl *et al.* (2012), Guo *et al.* (2017) and Pezzuolo *et al.* (2018) have also developed 3D image technologies with the aim of obtaining a 3D image of the

whole animal, but many problems remain. Pezzuolo *et al.* (2018), with low-cost portable equipment based on the Microsoft Kinect v1 sensor, concluded that their method still requires a lot of engineering to enable the automatic collection and extraction of data satisfactorily. A new device (called "Morpho3D") has been developed to easily capture the complete shape of cows and measure their morphological traits. Measurements obtained with this device were compared with values collected directly from live animals. To validate the method, repeatability and reproducibility were also analysed.

Materials and methods

Device

The device tested was installed in the dairy experimental farm of INRA-UMR PEGASE located in Le Rheu (France). This system comprises a total of five camera sensors, each in combination with a laser projector 650 nm wavelength to limit the risks to humans and animals. The pairs 'camera-laser' are installed on a mobile portico (Figure 1), set at 0.40 and 1.77 m above the ground on both sides and a fifth in the middle of the top of the portico. It moves at an average speed of 0.5 m s^{-1} from back to front and returns to its original position at an average speed of 0.3 m s^{-1}. The images are recorded during Phase 1: 80 photos per second and per camera. To secure the entire device, four stainless steel cables mark the movement of the cows. Animals can also be blocked by a self-locking head door if necessary.

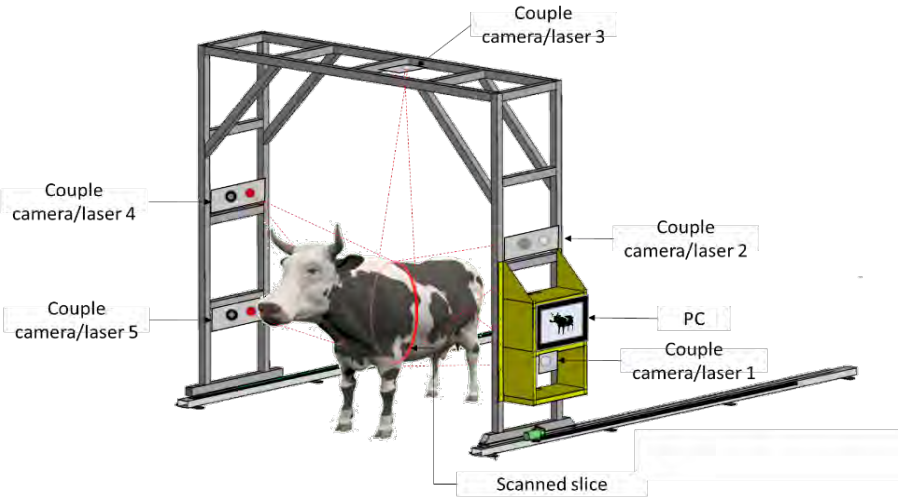

Figure 1. The Morpho3D scanning system

The images of the laser bands projected on the animal are captured by their corresponding camera and sent to a computer to reconstruct the 3D information. The images of each camera are first processed to build point clouds and the complete 3D reconstruction of the animal is performed by recording and merging the multiple views of the 3D data from the point clouds of the five camera-laser pairs (Figure 2). A distance threshold is set to ignore points too far from the camera and not belonging to the animal. An example of the living animal process is available at https://vimeo.com/219370900.

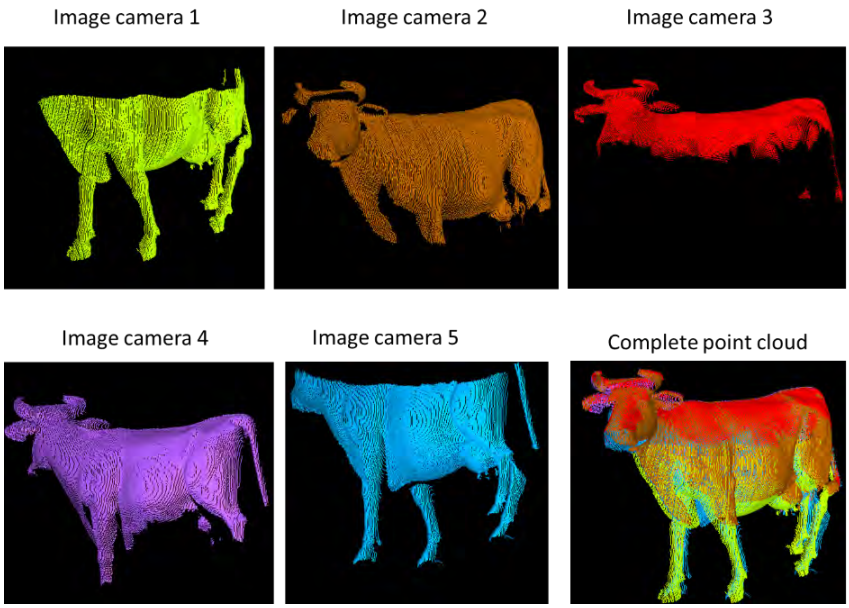

Figure 2. Point cloud reconstruction

Free software for processing and editing 3D triangular meshes was then used to clean the data (Meshlab *et al*, 2008). A Poisson surface reconstruction algorithm was applied to construct a triangulated mesh and shape smoothing (Kazhdan and Hoppe, 2013). The different stages of the treatment are shown in Figure 3.

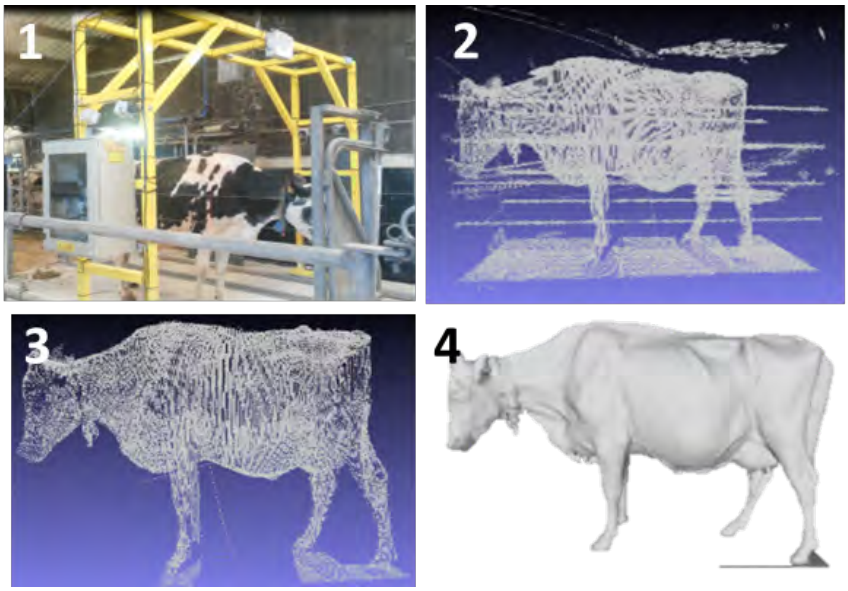

Figure 3. From Acquisition to Final Data: Image 1: Data Acquisition. Image 2: Raw cloud. Image 3: Cloud after Cleaning. Image 4: Final Image after Normalization and Poisson Reconstruction

Animals and measures

Data were collected between May and June 2017 on 30 Holstein dairy cows, aged 3.0 (+1.2) years on average, producing 25.5 (+3.6) kg of milk per day. These 30 cows were used to estimate the accuracy and correlations between the measurements made on the images of the new device ('Morpho3D') and those collected directly on the animals ('Manual'). For both methods ('Morpho3D' and 'Manual'), six of these 30 cows underwent a series of repeated measurements of the same indicators (six times each), in order to estimate the reproducibility of the methods. For the estimation of repeatability, a plastic cow model was used. The indicators measured on live animals and images included wither height (WH), heart girth (HG), chest depth (CD), hip width (HW), thirl width (TW) and ischium width (IW). For manual measurements, a tape and a measuring rod were used. In the reconstructed images, measurements were made using dedicated software (Metrux2α®, 3D Ouest).

Data analysis

To characterise the properties of the device and validate it, the measurements collected on the device were compared with those made manually. Repeatability and reproducibility of the methods were evaluated. Repeatability makes it possible to evaluate the error generated when estimating an indicator several times on the same sample with the same methodology, in the same environment, over a short period of time. It was estimated by making measurements six times the same day, from the same 3D scan of the same animal (plastic model cow). Reproducibility evaluates the same error but under varying environmental conditions. It was estimated with six cows scanned six times each the same day, with only one measurement per 3D image. The 3D variations were corrected to account for the effect of animals in extracting ANOVA model residues. The coefficients of variation for repeatability (CV_r) and reproducibility (CV_R) were evaluated as $CV_r = (\sigma r / \mu r) * 100$ and $CV_R = (\sigma R / \mu R) * 100$, where σr and σR are, respectively, the standard deviations of the corrected 3D measurement for the repeatability and reproducibility datasets, and μr and μR are, respectively, the average 3D measure of the repeatability and reproducibility data. Similarly, the repeatability and reproducibility of manual measurements were estimated by correcting the variability of the measures for the effect of cows and operators (two operators performed the same measures). The Anova 1 model then included "cow identity" as a factor in case of repeatability, and the Anova 2 model includes "cow identity" and "expert identity" as explanatory factors of the measure for reproducibility. The correlation analysis between the 3D image measurements and the reference values was performed using the statistical software R, version 3.0.2 (2013) and the analyses concerning repeatability and reproducibility were carried out with the SAS software (SAS Institute, 2016).

Results and discussion

Comparison of measurements manually performed on 30 cows or made from 3D images shows that most manual measurements have values lower than those obtained from 3D images (Table 1). The highest difference was observed for the ischium (difference of 11.2%), while the lowest was noted for the withers height (1.3%).

Table 1. Comparison of measurements manually performed on 30 cows or made from 3D images

Measure, cm	Manual	Morpho3D	P value
Heart girth (HG),	207.5	221.5	< 0.0001
Chest depth (CD)	79.4	83.8	< 0.0001
Wither height (WH)	146.9	148.8	< 0.003
Hip width (HW)	55.5	54.4	< 0.02
Thirl width (TW)	51.9	54.4	< 0.008
Ischium width (IW)	17.4	19.6	< 0.02

The correlation between the two types of measurements made is also very good (Table 2). The highest values are observed for chest depth (0.89) and the lowest values for ischium width (0.63). The prominent bones at the hips certainly explain the small differences observed between manual measurements and Morpho3D, as noted by Pezzulo *et al.* (2018). On the contrary, the prominent bones are less visible for the ischium, which may explain the meagre performance at this level. For some measurements (heart girth or chest depth), an overestimation exists because in some cases, the position of the front leg on the image did not allow a satisfactory access. The correlation values between the two approaches are generally lower than those reported by Buranarkal *et al.* (2012) and Pezzulo *et al.* (2018). Buranarkal *et al.* (2012) performed their measurements under laboratory conditions and used visual markings stuck on animals, unusable under commercial conditions. Pezzulo *et al.* (2018) performed their analyses on mean values.

Table 2. Coefficient of correlation and P-value, between manual measurements and those obtained on 3D images

Measure, cm	Coefficient of correlation	P value*
Heart girth (HG)	0.78	< 0.001
Chest depth (CD)	0.89	< 0.001
Wither height (WH)	0.62	< 0.001
Hip width (HW)	0.80	< 0.001
Thirl width (TW)	0.76	< 0.01
Ischium width (IW)	0.63	< 0.01

* test of Student

The repeatability and reproducibility values are quite similar between methods (Table 3). For data from 3D images, the σr ranged from 0.34–1.89 (CV 0.26–9.81) and σR from 0.55–5.87 (CV from 0.94–7.34). Using manual measurements, the σr ranged from 0.21–1.32 (CV 0.11–10.30) and σR ranged from 0.49–1.19 (CV 0.42–4.46). According to Fischer *et al.* (2015), measurement methods with repeatability and reproducibility CVs below 4% can be considered as interesting methods, which is the case in this study. Many authors stress the important effect of the animal's position on the fluctuations of the measurements made and the importance of selecting, often manually, the best images to limit undesirable variations (Kmet *et al.*, 2000; Stajnko *et al.*, 2008). Fischer *et al.* (2015) also showed that among the work done on BCS imaging estimation. But only a few authors went so far as

to qualify (repeatability, reproducibility) the method tested. These values are not generally available in most published studies.

Another important point that can change the quality of the images, and therefore ultimately the repeatability and reproducibility of measurements, is the environment (Tscharke & Banhazi, 2013). Indeed, most technologies are sensitive to daylight and are conducted in controlled light conditions. Similarly, the control of animal movements to obtain exploitable images is a crucial point. Work is still needed to ensure that devices developed under controlled conditions can be used in the 'aggressive' environment of a commercial farm, or at least an experimental farm.

An estimate of the time spent per method to obtain all the values of the indicators used was carried out and corresponded to 2.5 and 15 minutes for the manual and automatic systems. In the second case, the acquisition is fast (6 s on average) but the time needed to analyse and get the final results was about 14 min. It is clearly possible to reduce this time in the future through the optimization of models and equations.

Table 3. Repeatability and reproducibility of body measurements obtained directly from animals (Manual) or 3D images (Morpho3D). A plastic cow model was used for the repeatability study and six cows were used for the reproducibility study

Measure μr (cm)		**Repeatability**			**Reproducibility**		
		σr	CVr (%)	μR (cm)	σR	CVR (%)	
Heart girth (HG)	Manual	194.2	0.21	0.11	204.2	0.86	0.42
	Morpho3D	195.8	1.89	0.97	221.1	5.87	2.63
Chest depth (CD)	Manual	75.1	0.42	0.56	79.1	0.49	0.62
	Morpho3D	76.5	0.44	0.58	84.4	0.92	1.09
Wither height (WH)	Manual	129.1	1.04	0.80	148.9	1.07	0.72
	Morpho3D	131.1	0.34	0.26	148.6	2.12	1.42
Hip width (HW)	Manual	39.8	0.35	0.88	55.5	1.01	1.82
	Morpho3D	39.9	0.67	1.68	58.6	0.55	0.94
Thirl width (TW)	Manual	50.9	0.36	0.71	50.8	1.19	1.82
	Morpho3D	52.6	0.34	0.64	55.5	1.82	3.28
Ischium width (IW)	Manual	12.8	1.32	10.30	17.3	0.77	4.46
	Morpho3D	17.5	1.78	9.81	15.4	1.13	7.34

CVr and CVR are respectively the coefficients of variation for repeatability (CVr) and reproducibility (CVR), σr and σR the standard deviations of the corrected 3D measurement for the repeatability and reproducibility datasets and μr and μR the average 3D measurement of the repeatability and reproducibility data

Conclusion

This new technology is very promising. Despite a longer time of obtaining the final result, the 'animal handling' part is very short, and therefore can limit the risk of accidents for humans and animals, which is interesting for other production systems where the handling of animals is more delicate (suckler cattle, for example). The automation of the various phases of the acquisition process (cleaning, reconstruction and automatic measurement) will allow

to consider in the long term a use on a larger scale, as well as for the development of a new technology based on a 'one shot' image, where moving animals is no longer a problem. The possibility of obtaining a 3D image of the whole animal makes it possible to consider many valuations: automatic BCS, automated morphological score for animal selection, estimation of body weight, measurement of the surface and / or the volume of the animal.

Acknowledgements

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References

Bercovich, A., Edan, Y., Alchanatis, V., Moallem, U., Parmet, Y., Honig, H., Maltz, E., Antler, A., Halachmi, I. (2013). Development of an automatic system for cow body condition scoring using body shape signature. *Journal of Dairy Science*, 96(12): 8047–8059.

Buranakarl, C., Indramangala, J., Koobkaew, K., Sanghuayphrai, N., Sanpote, J., Tanprasert, C., Phatrapornnant, T., Sukhumavasi, W., Nampimoon, P. (2012). Estimation of body weight and body surface area in swamp buffaloes using visual image analysis. *Journal of Buffalo Science*, 1: 13–20.

Cignoni, P., Callieri, M., Corsini, M., Dellepiane, M., Ganovelli, F., Ranzuglia, G. (2008). MeshLab: an open-source mesh processing tool. *In: Sixth Eurographics Italian Chapter Conference*, pp. 129–136.

Fischer, A., Luginbuhl, T., Delattre, L., Delouard, J.M., Faverdin, P. (2015). Rear shape in 3 dimensions summarized by principal component analysis is a good predictor of body condition score in Holstein dairy cows. *Journal of Dairy Science,* 98: 4465–4476.

Guo, H., Ma, X., Ma, Q., Wang, K., Su, W., Zhu, D. (2017). LSSA_CAU: an interactive 3d point clouds analysis software for body measurement of livestock with similar forms of cows and pigs. *Computers and Electronics in Agriculture*, 138: 60–68.

Kmet, J., Sakowski, T., Huba, J., Peskovicova, D., Chrenek, J., Polak, P. (2000). Application of video image analysis in the slaughter value estimation of live Simmental bulls. *Archiv Tierzucht Dummerstorf,* 43: 411–416.

Kuzuhara, Y., Kawamura, K., Yoshitoshi, R., Tamaki, T., Sugai, S., Ikegami, M., Kurokawa, Y., Obitsu, T., Okita, M., Sugino, T., Yasuda, T. (2015). A preliminarily study for predicting body weight and milk properties in lactating Holstein cows using a three dimensional camera system. *Computers and Electronics in Agriculture,* 111: 186–193.

Heinrichs, A.J., Hargrove, G.L. (1987). Standards of weight and height for Holstein heifers. *Journal of Dairy Science*, 70: 653–660.

Marchant, J.A., Schofield, C.P. (1993). Extending the snake image processing algorithm for outlining pigs in scenes. *Computers and Electronics in Agriculture*, 8: 261–275.

Negretti, P., Bianconi, G., Bartocci, S., Terramoccia, S., Verna, M. (2008). Determination of live weight and body condition score in lactating Mediterranean buffalo by Visual Image Analysis. *Livestock Science*, 113: 1–7.

Pezzuolo, A., Guarino, M., Sartori, L., Marinello, F. (2018a). A feasibility study on the use of a structured light depth-camera for three-dimensional body measurements of dairy cows in free-stall barns. *Sensors,* 18: 673. https://doi.org/10.3390/s18020673.

R Core Team (2013). R Foundation for Statistical Computing, Vienna, Austria.

SAS institute. (2016).

Schofield, C.P., Marchant, J.A., White, R.P., Brandl, N., Wilson, M. (1999). Monitoring of pig growth using prototype imaging system. *Journal of Agricultural Engineering Research*, 72(3): 205–210.

Stajnko, D., Brus, M., Hocevar, M. (2008). Estimation of bull live weight through thermographically measured body dimensions. *Computers and Electronics in Agriculture*, 61: 223–240.

Tscharke, M., Banhazi, T.M. (2013). Review of methods to determine weight and size of livestock from images. *Australian Journal of Multi-Disciplinary Engineering*, 10: 1–17.

Session 4

Precision Livestock Farming Data and its Exploitation for Solutions and Decision-making (2)

Cow's Own Worth (C.O.W.) - Precision in identifying the performance of your dairy cows

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Abstract

The ability to accurately identify cows with the highest future profit potential has become more difficult in larger dairy herds which has amplified the need for precision-based technologies. The Cow's Own Worth (C.O.W.) is a new decision support tool, available through the HerdPlus web application or online account, to aid herdowners in making informed decisions on dairy females for culling and retention. C.O.W. ranks dairy females on expected profit for the remainder of their lifetime, specifically considering the genetic merit, permanent environmental effects, current states of the individual (i.e. calving date and parity), as well as predicting future performance in fertility, survival and somatic cell count. The theoretical framework of C.O.W. has been described previously by Kelleher *et al.* (2015). C.O.W. generates real-time rankings of each cow within the herd using the Irish Cattle Breeding Federation Oracle Exadata database. Each procedure is executed based on the most up-to-date information stored within the database. The objective of this study was to validate the performance of C.O.W. using herds that have actively logged onto the online service in 2018. Phenotypic performance records were used from 1,528 herds and 175,695 cows which accounts for 25% of the national milk recorded herd. Cows were stratified per quartile on C.O.W. value within herd. The top 20% on C.O.W. yielded 1,133 kg more milk and 124 kg more milk solids compared to the bottom 20% contemporaries. The quality and timely entry of data is crucial for the precision and accuracy of C.O.W. and benefits the industry by offering added value to existing services and increasing accuracy of genetic evaluations and key performance indicators.

Keywords: culling, genetics, database, decision support

Introduction

The accurate identification of the highest profit potential dairy cows within herd has become increasingly more difficult due to the expansion of herd size in Ireland in recent years. The decision to cull cows that are no longer profitable from the herd has a substantial impact on the herd profitability. This has amplified the need for precision-based technologies to aid herdowners in choosing the most optimal strategy to identify culling candidates within their herd.

The Irish Cattle Breeding Federation (ICBF) operates a centralised database for all cattle herds in Ireland for the provision of running the national genetic evaluations and providing cattle breeding services. The Cow's Own Worth (C.O.W.) is a decision support tool available to herdowners through the ICBF's subscription service, HerdPlus, through web application and subscriber's online account with the purpose of ranking dairy cows on expected profitability using multiple sources of live data stored in the database. Herdowners make significant investments in animal events data recording (e.g. milk recording, pregnancy diagnosis and genotyping) but collating all these data sources into one value per animal is key to aid decision making. The C.O.W. generates an expected profitability value for every cow for the remainder of every dairy female's life within a herd and ranks cows using additive genetic merit (estimated breeding values), non-additive genetic merit, permanent environment effects and current states of the cow (i.e. lactation number, calving date,

and predicted calving date from available inseminations or pregnancy diagnosis). The C.O.W. profile runs instantly, combining all information and executing each procedure on the most up-to-date information to generate a ranking for the dairy cows within herd, allowing the herdowner to quickly identify under-performing dairy females to cull, thereby retaining only the most profitable females. Other benefits of this management tool are the reductions in time, effort and resources farmers spend on culling and retention decisions while getting more value from their data recording strategies.

The C.O.W. has been in operation since October 2017 and an opportunity exists to validate the accuracy and usefulness of such a precision tool by analysing the herds that have used the C.O.W. over a period of 12 months. The objective of this study was to validate the performance of C.O.W. using herds that have actively logged onto the online service in 2018.

Material and methods

Data

A sample of herds that had accessed C.O.W. during a 12-month period since the launch of C.O.W. were extracted from the ICBF database. Phenotypes for milk production, SCC and calving records were also extracted for 2018. Individual animal EBV for traits included in the EBI, from the domestic genetic evaluations were used. Permanent environmental effects were available from the genetic evaluations for test-day milk, fat and protein field, as well as SCS (natural logarithm of SCC). Heterosis and recombination loss coefficients for each animal and their respective regression coefficients associated with each of the performance traits were also available for all traits included in the national genetic evaluation. Economic values were taken from the Moorepark Dairy Systems Model (MDSM; Shalloo *et al.,* 2004) and updated for a prevailing milk price (30.5c/l) and future price scenario (30.5c/l).

Index evaluation

Individual cow EBI values and C.O.W. values from the national genetic evaluations were analysed from cows that were ranked on the C.O.W. Cows were categorised, within herd, into five groups based on their value for either the C.O.W. or EBI index. Only cows that had phenotypic performance data for milk production traits (milk yield, fat yield, protein yield, and SCC) were retained. After editing, C.O.W. values and EBI values, as well as phenotypic performance data, were available on 175,695 cows in 1,528 herds which accounts for 25% of the national milk recorded herd.

Results and discussion

The top 20% on C.O.W. yielded 1,133 kg more milk and 124 kg more milk solids compared to the bottom 20% contemporaries on C.O.W. (Figure 1). The relative differences for the respective traits, between the top and bottom 20% stratified on EBI were less compared to when stratified on C.O.W. The top 20% on EBI yielded 386 kg more milk and 67 kg more milk solids compared to the bottom 20% contemporaries on EBI. The C.O.W. is not a proposed replacement for the EBI. The relative differences in Figure 1 reflects the efficient precision of the C.O.W. in ranking cows on expected performance due to considering not only additive genetic merit but also additional factors that impact on animal performance, for example, non-additive genetic merit, permanent environmental effects and transition probabilities for fertility performance (Kelleher *et al.,* 2015). Cows that rank lower on C.O.W. have lower production and therefore have a lower expected profitability, all else being equal, within the herd.

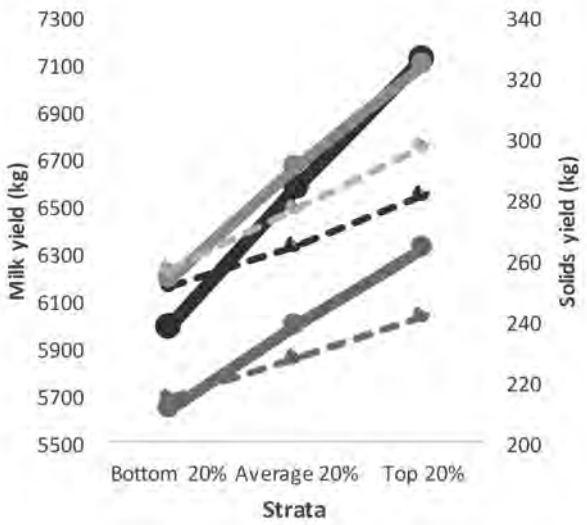

Figure 1. Least squares means for 305D milk (blue), fat (green) and protein (red) yield for the bottom 20%, average 20% and top 20% of animals ranked on C.O.W. (solid line) or EBI (dash line)

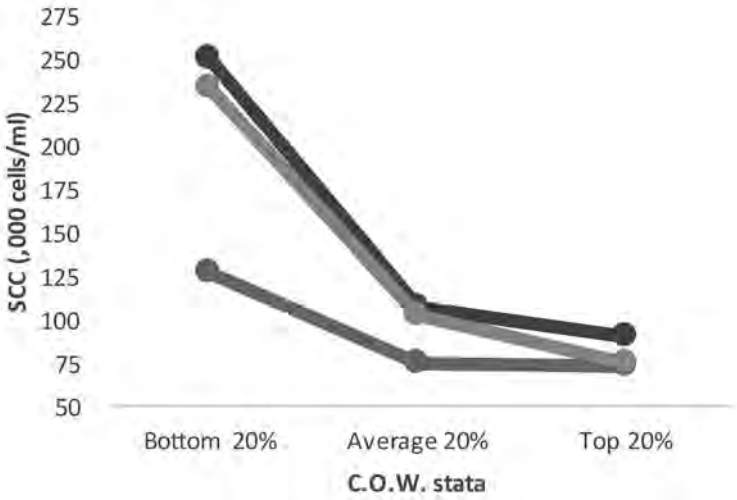

Figure 2. Least squares means for SCC for parity 1 (blue), 3 (red) and 5+ (green) for the bottom 20%, average 20% and top 20% of animals ranked on C.O.W. (solid line)

Furthermore, a similar trend is illustrated in Figure 2 where average SCC is higher in cows ranked lower on the C.O.W. in all parities. Finally, cows calving earlier in the spring were more likely to rank higher on the C.O.W. Therefore, the stratification of the C.O.W. has highlighted the significant differences in cow performance in terms of production, fertility and health traits. Cows ranking higher on C.O.W. have more milk yield and solids, calve earlier in the season and have lower SCC.

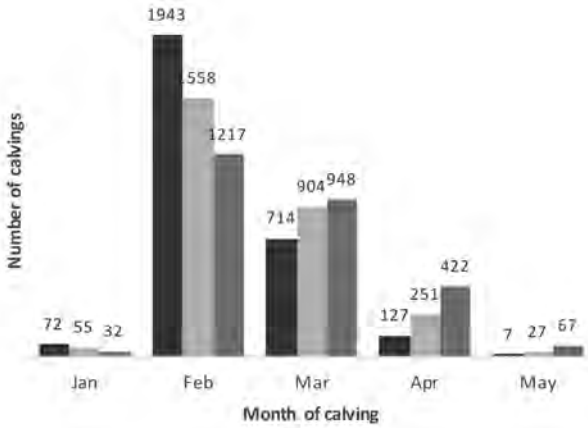

Figure 3. Month of calving frequencies for the top 20% (blue), average 20% (green) and bottom 20% (red) on the C.O.W.

Conclusions

Tools already exist to identify dairy females as suitable parents of the next generation. The C.O.W. is a new precision management tool to rank dairy females for culling decisions. The C.O.W. has been available for commercial use since October 2017. C.O.W. integrates multiple sources of available data, and critically, is complementary to the EBI (Ireland's national breeding index) which identifies the most suitable females for breeding replacements. The C.O.W. offers future prospects to improve herd profitability by efficiently and scientifically identifying the least profitable cows to remove from the herd. The web application and online C.O.W. service thereby adds value to existing services such as milk recording and genotyping of dairy females and provides additional information to herdowners to aid in informed management decisions in real-time.

References

Kelleher, M.M., Amer, P.R., Shalloo, L., Evans, R.D., Byrne, T.J., Buckley, F. and D.P. Berry. (2015). Development of an index to rank dairy females on expected lifetime profit. *Journal of Dairy Science,* 98: 4225–4239.

Shalloo, L., Dillon, P., Rath, M., and M. Wallace. (2004). Description and validation of the Moorepark Dairy System Model. *Journal of Dairy Science,* 87: 1945–1959.

Using a data lake in animal sciences

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Abstract

In the livestock domain, Big Data is becoming more common and is being anchored into the mind-set of researchers. With the increasing availability of large amounts of data of varying nature, there is the challenge of how to store, combine, and analyse these data efficiently. With this study, we explored the possibility of using a data lake for storing and analysing sensor data, using an animal experiment as the use case, to improve scalability and interoperability. The use case was an experiment within Breed4Food (a public-private partnership), in which the gait score of 200 turkeys was determined. In the experiment, a gait score was traditionally assigned to each animal by a highly-skilled person who visually inspected them walking. Next to it, a set of sensor data streams was recorded for each animal, specifically inertial measurement units (IMUs), a 3D-video camera, and a force plate, with the ambition to explore the effectiveness of these data streams as predictors for estimating the gait score. The resulting sensor output, i.e. raw data, were successfully stored in its original format in the data lake. Subsequently, for each sensor output we performed extract, transform, and load activities, by executing custom-made scripts to generate tab or comma separated files. Lastly, by using Apache Spark it was possible to easily perform parallel processing of the data, allowing for fast computing. In conclusion, we managed to set up a data lake, load animal experimental data and run preliminary analyses. The data lake allowed for easy scale up of both data loading and analyses, which is desired for dynamic analyses pipelines, especially when more data are collected in the future.

Keywords: data lake, sensor data, animal experiment, scalability

Introduction

Traditionally, animal scientists work with structured relational databases to store data used in their research. However, ongoing technological innovations and their implementation results in a whole generation of unstructured non-relational data, i.e. camera or video images, and the quantity of data is increasing simultaneously too. With the increasing availability of large amounts of data with varying nature, there is the challenge of how to store, combine, and analyse these data efficiently. In the information computation technology world there seems to be a move from structured relational databases to schema-less databases (commonly referred to as NoSQL databases) for management and storage of data; and from data warehouses to data lakes. The key driver behind this transition is that we need to store the source data and handle ever increasing datasets, varying data structures, as well as heterogeneous and multimodal data. To this end, the process of data pre-processing, i.e. the extract, transform, and load (ETL) procedure becomes more demanding.

With this study, we explored the possibility of using a data lake for storing and analysing sensor data, using an animal experiment as use case, to have improved scalability and interoperability. In this experiment, three different sensors were used to capture (indices) of the gait score of turkeys. The three sensors used were 1) inertial measurement units

(IMUs), 2) a 3D-video camera, and 3) a force plate. The raw output of these three sensors were stored in the data lake and the ETL procedure was applied by employing custom scripts to make the data more aligned with FAIR-principles.

Material and methods

Data lake

The deployment of a data lake involves the installation and management of several big data software tools, including reliable distributed file systems, cluster resource management and execution environments for map reduce, data flows, SQL, such as Apache Spark. To avoid the overheads of this task, we reused a predefined software stack, available as a Docker container. This involved three major steps: First, we installed Docker, which is a computer program supporting operating-system-level virtualization, also known as containerization. A container consists of a standard unit of software and its dependencies so the application can run quickly and reliably from one computing environment to another. Second, we downloaded an image from Docker (https://hub.docker.com/r/jupyter/all-spark-notebook/), here we selected the 'jupyter/all-spark-notebook'. This notebook includes Python, R, and Scala support for Apache Spark. By doing so, we ensured a flexibility to employ different scripting languages, and not to limit ourselves to one scripting language. Third, we developed and executed custom scripts (in Python and C++) via Jupyter Notebook (http://jupyter.org/) and for visualization we used IBM PixieDust. An overview of the software used is given in Figure 1.

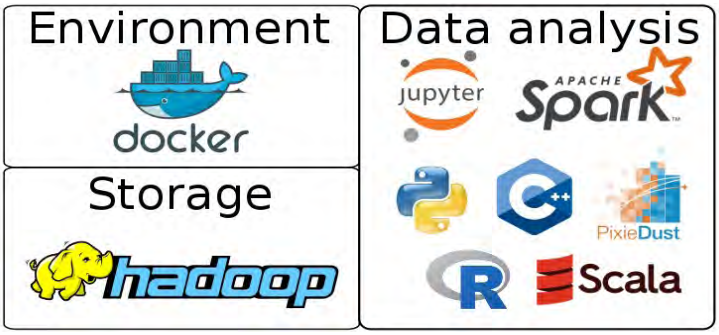

Figure 1. Overview of the software used in our data lake

Case study

Within the Breed4Food-Locomotion project, data from several sensors were collected during an animal experiment investigating the gait score of turkeys. These sensors included camera depth images (Intel Realsense D415), one force plate (Kistler), and three Inertial Measurement Units (Xsense MTw Awinda). These three IMUs were placed at the bird's legs (one each), and one IMU was placed on the bird's torso. Sensor-borne data were ingested to the data lake in raw format and stored using a Hadoop Distributed File System (HDFS). Sensor data of two selected sensors were binary data, i.e. force plate data (.tdms) and accelerometers (.mtb). In contrast, the raw output of the 3D-cameras was a bag file, this is a file format in Robot Operating System (ROS) for storing a sequence of records. Here we used the Melodic Meriona version of ROS to extract the data we needed for further processing.

ETL (Pre-processing and storage)

We generated customised scripts to convert the raw formats of each sensor to prepare these files for downstream analyses, see also Figure 2. For the force plate data, the technical data

management solution (.tdms) files were converted to comma separated values (.csv) files via the cross-platform Python package npTDMS. The npTDMS package is created to read and write TDMS files as produced by LabVIEW. For the extraction of the accelerometer files (.mtb files), a C++ script was used to automatically extract the information and convert this to a .csv file. Lastly, the information from the 3D-cameras (.bag files) were extracted by using a custom-made Python script that links to the ROS.

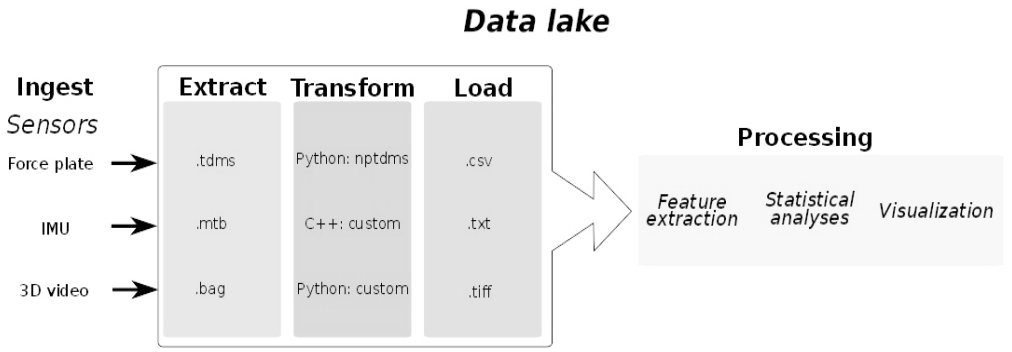

Figure 2. Flow diagram of the 'Extract, Transform, and Load' procedure of the data lake

Results and discussion

Data lake

In animal sciences a plethora of data are generated and is expected to continue in the (near) future. Important aspects to take into account include how to ingest (the process of moving data into a distributed file system), store, process, and access these data. In the current study, we explored a data lake in which raw sensor data were collected and ingested, and subsequently transformed and visualised to investigate the benefits of a data lake approach, and to identify possible caveats of this approach compared to the more traditionally used structured and relational data bases.

Building and managing

Before starting to work with a data lake, some prerequisites are needed, like virtualization on your computer should be allowed. The advantage of building a data lake is that it can be exploited, for example, when an (animal) experiment encompasses large volumes of data and it is necessary to scale-up the data ingestion. To this end, we built a customised data lake, designed to ingest the three types of sensor data, i.e. force plate, accelerometers (IMU), and 3D-video. The final deployable container image, an executable package including all necessary files, of the data lake was generated after multiple iterations. These iterations, although a labour intensive job, are of great importance because for scaling up this image needs to be deployed to many machines with no margin of error. The final image contained all necessary software and applications, as well as their dependencies, which was needed for transforming the animal experimental data that subsequently could be loaded in different programming languages, like Python and R. We could ingest and perform the ETL procedure for all animals at once and pre-process these data for further applications, analyses, and visualization. For example, all data was stored in its original format, allowing for extraction of alternative features in the future. Processing after a series of commands has been optimised and parallelised by the Apache Spark engine in the background. Another example is the possibility to link the different sensors, i.e. feature extraction of interest, in an analysis pipeline and subsequently perform statistical methods, e.g. linear regression.

Another important aspect associated to deploying a data lake that we encountered was the possible skills gap. For building and managing a container image, knowledge is required about command line code (such as Linux and/or Bash) and other programming languages (including Julia, Perl, and Python). This skills gap in people has already been identified (Gesing *et al.*, 2015, Connor *et al.*, 2016, Gibert *et al.,* 2018) and finding and maintaining people with the proper skill set is often more difficult in organisations compared to 'processes' and 'technology'. In practice, this means that there is a shortage of persons with the necessary skills, this is also observed within the animal sciences domain, where to our knowledge not much effort is (yet) put into data lakes, and big data technologies, in general. Thus, to adopt such approaches, investments need to be made, especially in acquiring the skills. Simultaneously, a start needs to be made by translating and adopting today's challenges in the data lake approach. For example, by initiation of embedding this data lake approach into education of (MSc and) PhD students, and especially into animal experimentation. For the latter, it is expected that in the near future, data from animal experimentation will become larger in volume and more complex. Compared to data warehouses, data lakes have a flexible configuration and high agility, as well as up to 10–100 times less expensive to deploy compared to conventional data warehousing (Stein & Morrison 2014, Khine & Wang 2018). Moreover, for precision livestock farming where it is expected that sensor data will become real-time in the (near) future, ingestion and storage of large volumes of data, can be performed immediately by a data lake approach. In our case study, the biggest challenges were the data transformations, due to the encrypted raw file formats from the different sensors. Nevertheless, we managed to overcome this by branching out to domain experts.

Metadata

Metadata is exceptionally important for managing your data lake. This encompasses both the earlier mentioned versioning of software and packages, as well as the description of the different data types, how these data were measured and under which circumstances. Generating such metadata is essential, as without effective metadata, data that streams into a data lake may never be seen again. Another important aspect getting more attention lately, is the Findable, Accessible, Interoperable and Reusable (FAIR) Guiding Principles (Wilkinson *et al.*, 2016). For our data lake, we primarily focused on the accessibility of the data, using open source scripts and customise them to our data lake. By generating Jupyter Notebooks with extensive descriptions of the various commands, it will be possible for other persons to reuse the data and scripts. However, more importantly, the various scripts could be read and executed by linking to other computers. In the current case study, we have generated a 'closed', IP-protected, FAIR data point, because we collaborate with an industry partner in the breeding sector.

Conclusions

The main lesson learned was that with a data lake approach it is possible to capture and maintain the entire universe of data from, e.g. an animal experiment in one virtual location (i.e. a container image). In addition, there is no data loss and the data are stored in raw format. This opens the possibilities to revisit the data and perform alternative pre-processing fitting novel or different hypotheses to the original stated hypothesis. Lastly, the whole procedure to extract, transform, and load (ETL-procedure) is scalable and could therefore reduce computing time, which is desired for dynamic analyses pipelines.

Acknowledgements

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References

Connor, C., A. Jacobson, A. Bonnie and G. Grider (2016). An Innovative Approach to Bridge a Skill Gap and Grow a Workforce Pipeline: *The Computer System, Cluster, and Networking Summer Institute. {USENIX} Journal of Election Technology and Systems,* ({JETS}) 2(1).

Gesing, S., T.R. Connor and I.J. Taylor (2015). Genomics and Biological Big Data: Facing Current and Future Challenges around Data and Software Sharing and Reproducibility. CoRR abs/1511.02689.

Gibert, K., J.S. Horsburgh, I.N. Athanasiadis and G. Holmes (2018). Environmental Data Science. *Environmental Modelling & Software*, 106: 4–12.

Khine, P.P. and Z.S. Wang (2018). Data lake: a new ideology in big data era. ITM Web of Conferences, EDP Sciences.

Stein, B. and A. Morrison (2014). The enterprise data lake: Better integration and deeper analytics. PwC Technology Forecast: Rethinking integration, 1(1-9): 18.

Wilkinson, M.D., M. Dumontier, I.J. Aalbersberg, G. Appleton, M. Axton, A. Baak, N. Blomberg, J.W. Boiten, L.B. da Silva Santos, P.E. Bourne, J. Bouwman, A.J. Brookes, T. Clark, M. Crosas, I. Dillo, O. Dumon, S. Edmunds, C.T. Evelo, R. Finkers, A. Gonzalez-Beltran, A.J. Gray, P. Groth, C. Goble, J.S. Grethe, J. Heringa, P.A. t Hoen, R. Hooft, T. Kuhn, R. Kok, J. Kok, S.J. Lusher, M.E. Martone, A. Mons, A.L. Packer, B. Persson, P. Rocca-Serra, M. Roos, R. van Schaik, S.A. Sansone, E. Schultes, T. Sengstag, T. Slater, G. Strawn, M.A. Swertz, M. Thompson, J. van der Lei, E. van Mulligen, J. Velterop, A. Waagmeester, P. Wittenburg, K. Wolstencroft, J. Zhao and B. Mons (2016). The FAIR Guiding Principles for scientific data management and stewardship. *Scientific Data,* 3: 160018.

Interactive insight in big livestock data

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Abstract

The vast amount of livestock (sensor) data collected everyday, offers a huge potential to improve model prediction and therefore decision support for farmers. However, the prediction performance of these models depends highly on the availability and quality of the data. Careful dataset preparation is therefore important. Nowadays, selecting and understanding the data becomes increasingly more difficult as the data grows in size and complexity. In our study we provide data providers within the livestock farming industry with guidelines to describe their data sets more accurately and provide model developers useful techniques to compose a good quality subset of the data to form the base for their model development. This all comes together into our Interactive Visualization tool which allows model developers to explore the data and select, visually or with the use of familiar programming languages, subsets of good quality data for modelling. By using state-of-the-art distributed computing frameworks, our prototype solution can scale as the size of the data grows to terabytes or even petabytes. We use operational (sensor) data from the Dutch smart dairy farming project to illustrate our solution.

Keywords: big data, dairy farming, interactive insight, dataset preparation, data quality

Introduction

Since as early as the 1980's, data acquisition and analysis has improved the health management of cows in the dairy industry with the use of a variety of sensors (Rutten *et al.*, 2013). However, young animals before their productive life (young stock rearing) have largely been excluded from the use of these IT techniques (Bahr *et al.*, 2016). With the project called 'Precision feeding of young calves facilitated by IoT and Big Data technologies', funded by the Dutch TKI program HTSM, researchers look how data-driven models can support the development of young stock rearing and thereby improve the future lifetime production of dairy cows. In the same project, we developed a tool to support these researchers in their development of data-driven models.

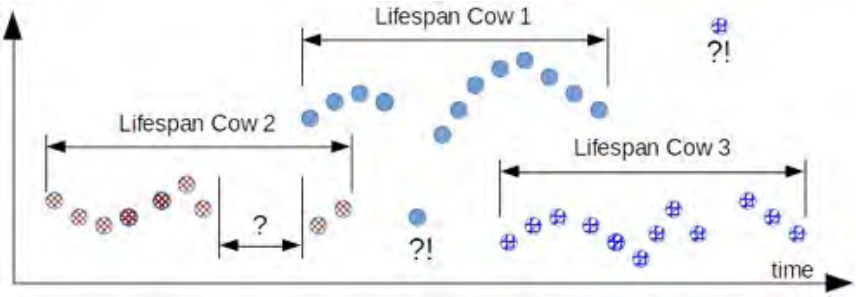

Figure 1. Raw sensor data is often noisy and imperfect. The data might contain gaps or invalid values as a result of malfunctioning sensors. Furthermore, different timelines often need to be realigned in time in order for them to be comparable

The prediction performance of data-driven models depends highly on the quality and availability of the data. Raw sensor information can be incomplete or invalid and data

from multiple sensors can be misaligned in time (see Figure 1) possibly resulting in a biased or poorly trained model. Datasets used for fitting or training the models therefore need to be selected with care, manually.

This careful dataset selection and preparation typically takes a large amount of time during model development (see Figure 2). This becomes increasingly more difficult and time consuming as the complexity and size of the data grows (e.g. dealing with Big Data).

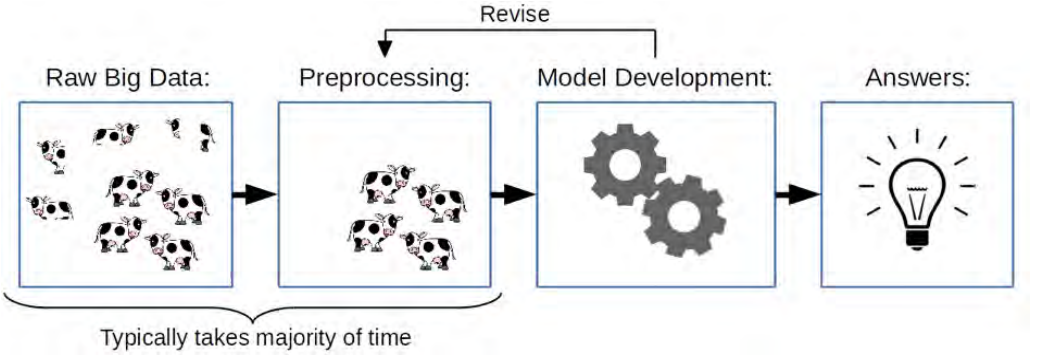

Figure 2. Dealing with large amounts of raw data and selecting and processing into a suitable subset typically takes a lot of time during the model development life cycle

In this article we present an Interactive Visualisation tool for model makers to reduce the time it takes to select an appropriate subset out of a raw dataset suitable for their data-driven modelling. As selection support we developed Quality Metrics and Data Summaries.

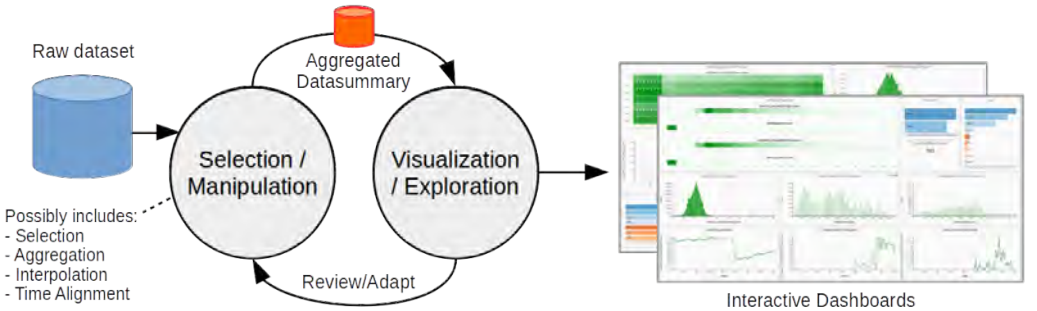

Figure 3. Typical usage workflow of our Interactive Visualization tool for the purpose of dataset preparation. See text for more details

Our tool assists the model developer in selecting a suitable subset of the raw dataset for modelling (see Figure 3). This typically involves two steps; a) selection and manipulation (either visually or using program code) of the dataset and b) exploration and validation of the selected subset using a visual front-end.

State of the Art

Solutions in dealing with the visualization of large amounts of data exist in current literature (Gorodov, Evgeniy Yur'evich Gubarev, 2013; Wang *et al.*, 2015). However, many implementations are very application specific or limited to the processing power of a single node (Liu *et al.*, 2013) and the more generic visualizations tools have their own limitations in terms of the amount of data they support (Ali *et al.*, 2016).

Methods

Design Criteria

For the purpose of our research and its aimed application (exploration and selection of promising datasets for developing a model), we defined the following design criteria:

- *Scalability:* the tool should be able to distribute its processing over the browser (thus providing visual interactivity) and on one or more servers which intelligently reduces the size of (too) large datasets into data summaries.
- *Data quality and availability:* the tool should provide insight into the quality (e.g. mean and standard deviation) and availability (e.g. frequency and time interval) of the data in a comparative way between different data subsets.
- *Time realignment:* the tool should be able to realign data subsets relative to a new time offset (such as the birthdate of an animal) or set of time offsets (such as the calving dates of a cow).

Quality Metrics and Data Summaries

Different aspects of the data can be visualised with the tool. We consider two groups of aspects: those describing the values in the dataset (e.g. count, mean, standard deviation, minimum/maximum value, etc.) and those describing the time distribution of the dataset (*e.g.* mean absolute deviation of time interval, minimum/maximum data point time interval, etc.). These aspects are called quality metrics and are an aggregation of the original larger dataset. We collect and store these different aggregations as data summaries.

The data summary can store quality metrics aggregated over different periods of time (e.g. hours, days, weeks, years, etc.) This is the resolution of the data summary. Next to this, the data summary also describes alignments. This could be either the absolute time of the measurement or relative to a specific time offset (e.g. birthdate) or a repeating timeline (e.g. multiple calving dates of a single cow).

The developed tool loads and visualizes the data summary. Since the data summary is based on aggregations, it typically contains less data compared to the original dataset and therefore is easier to store and faster to transfer to the dashboard and visualise.

System Overview

A system overview of the tool is shown in Figure 4 and consists of a distributed storage component, a processing component, an interface and two possible data refinement options. Raw data stored in storage is processed in a distributed way into sufficiently small data summaries (the contents of which depends on the selection made by the user) so that they can be visualised in the user interface.

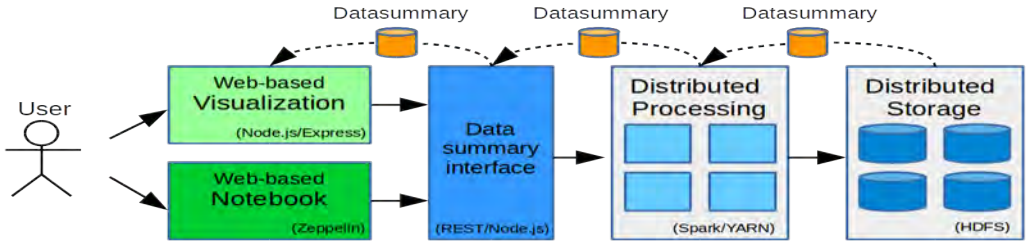

Figure 4. Overall architecture of the complete system. The solid lines indicate the order in which the different components are used during selection and manipulation of the data. The dashed lines indicate the way the data summaries are transferred. The technology used is shown within brackets. The user typically is a data scientist or model developer

Results

Dataset Used

During the Smart Dairy Farming (SDF) project, real-time operational sensor data from dairy cows was collected for several years and processed with models in order to develop work instructions for the seven farmers in the SDF project (Lokhorst & Wulfse, 2015). From two of these farmers we received consent to use their data for the development of the tool presented in this paper. To be precise: we used the data from farm three and seven as described in (Vonder *et al.*, 2015), containing sensor data for activity, water intake, milk intake, milk production, food intake and weight, for 359 animals in total.

Setup

During experimentation, the following configuration was used for the different elements described in the System Overview (see Figure 4). Both the storage and processing layers were distributed over four different machines.

- *Storage:* the original file-based data, as retrieved from the InfoBroker (Vonder *et al.*, 2015), is stored on a HDFS cluster (Borthakur *et al.,* 2008). This InfoBroker has been developed to provide interoperability and ease of data exchange among different existing (proprietary) sensor systems.
- *Processing:* to aggregate and process the data, Apache Spark (Zaharia *et al.*, 2016) is used as the processing framework on top of YARN (Vavilapalli *et al.*, 2013) for cluster resource management. Our custom library to create the data summaries was written in Scala. Apache Livy is used to support multitenancy for the same Spark Session.
- *Datasummary Interface:* a custom REST interface was made in Node.js (Tilkov & Verivue, 2010) to create and retrieve the data summaries.
- *Notebook:* Apache Zeppelin allows to select and manipulate the data directly using the Scala programming language.

Use-case Description

The benefit of using the tool is illustrated using the following use-case: A researcher in precision dairy farming (the user) is particularly interested in the development of young stock in the pre-weaning period. He wants to have a clear insight into the availability, amount and quality of all available data, in order to compose the best/biggest training set for his machine learning methods. In Figure 5 some of the available sensors are shown: 'milk intake', 'water intake', 'weight' (from two types of sensors) and 'activity'.

We can immediately see in Figure 5 (a) that there is data available for all four sensors, and also that we only have data for all five sensors *at the same time* in the period of January 2014 until July 2015.

The user (a researcher in precision dairy farming) aligns the data to the birthdate of each individual animal, as depicted in Figure 5 (b). As the researcher is interested in young stock rearing, he looks at first 125 days since birth of the animals. As can be seen in Figure 5 (b) for this period of time there is only data available for the sensors 'water intake', 'milk intake' and 'weight'.

Since that is the data the user could use for his research, he selects the first 125 days in the graph (see Figure 6). After this selection, the tool shows the remaining data for the four sensors on the left side (and only 'water intake', 'milk intake' and 'weight' have actual data). By pressing the download symbol (2nd symbol from the upper right corner in Figure 6), the actual datasets are selected and prepared for the user (for only these animals that have 'water intake', 'milk intake' and 'weight' data: 119 animals).

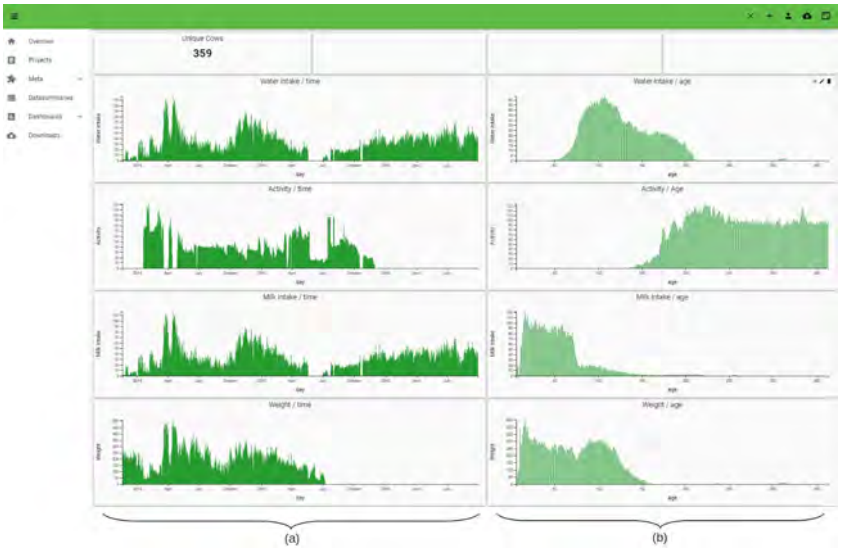

Figure 5. A screenshot of the interactive dashboard before selection. (a) The available data shown in absolute measurement time. The horizontal axis describes the absolute time (on a daily basis) and the vertical axis describes the number of measured values of each specific sensor (for all animals together). (b) The available data shown in relative time. The horizontal axis describes relative time (in days since birth of the animals) and the vertical axis describes again the number of measured values of each specific sensor (for all animals together) in the specific day since birth of the animals

In only a few mouse clicks the researcher was able to narrow down the complete data set of 359 animals to 119 calves with the relevant amount of data for his model development.

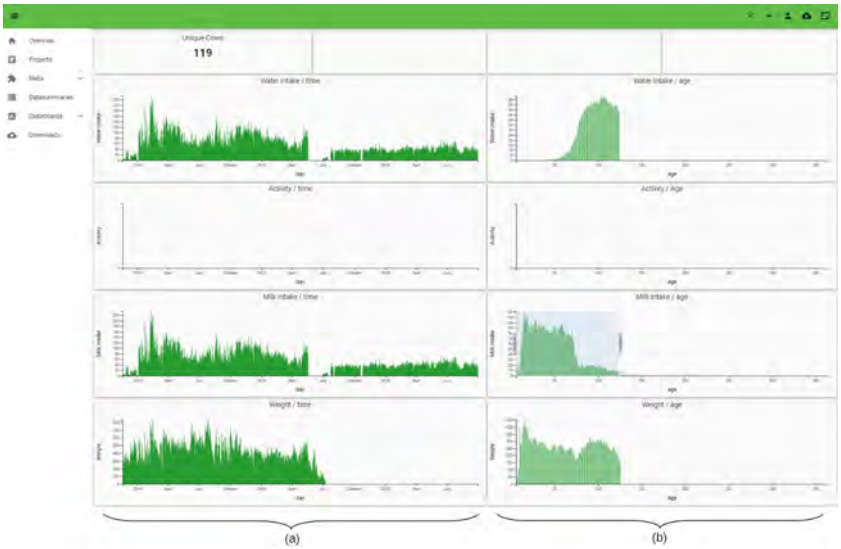

Figure 6. A screenshot of the interactive dashboard after selection. The available data shown in absolute measurement time (a), based on the selection (b) of the first 125 days since birth of the animals

Conclusions

Using our Interactive Visualization tool presented in this article, the user can aggregate (very) large datasets into small interpretable data summaries using quality metrics. The tool allows users to visualise, realign and select relevant parts of the complete dataset. This enables model makers to quickly narrow down their search in finding useful relevant sub selections of datasets that can be used in statistical modelling and machine learning. Using the tool allows model makers to save a lot of time and hassle by avoiding the need for manual selection and inspection of large quantities of data.

Future Work

To include better mechanisms to evaluate the quality of the data in large datasets, the tool could be extended with a set of more advanced statistical and machine learning methods, for example, to test the normality of the data or test for anomalies.

For our research, we created the data summaries directly from the raw data. We are currently working on a cookbook with guidelines for data providers to better describe their data and create the data summaries themselves. This could benefit the data providers in advertising the availability of the data while making it easier for the model developers to start their dataset selection.

There is a shift going on from traditional databases, to data warehouses, to data lakes and finally, to data spaces (Jarke & Quix, 2017) in which the actual location of the data becomes more fluid and data sovereignty becomes more important. This requires a different approach in the way data is accessed and represented. Although already quite flexible, the Interactive Visualization tool presented in this article should better meet the requirements of these data spaces in future research.

Acknowledgements

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References

Ali, S.M., Gupta, N., Nayak, G.K., & Lenka, R.K. (2016). Big data visualization: Tools and challenges. In:*Proceedings of the 2016 2nd International Conference on Contemporary Computing and Informatics, IC3I 2016*, pp. 656–660.

Bahr, C., Bruininx, E., & Van den Belt, A. (2016). Nutrition, sensors and genetics – a data driven smart feeding approach by Agrifirm. In C. Kamphuis & W. Steeneveld (Eds.), *Precision Dairy Farming 2016*, pp. 49–53. Wageningen Academic Publishers.

Borthakur, D., & others. (2008). HDFS architecture guide. *Hadoop Apache Project*, 53: 1–13.

Gorodov, Evgeniy Yur'evich Gubarev, V.V. (2013). Analytical Review of Data Visualization Methods in Application to Big Data. *Journal of Electrical and Computer Engineering*, *2013*, 12.

Jarke, M., & Quix, C. (2017). *On Warehouses, Lakes, and Spaces: The Changing Role of Conceptual Modeling for Data Integration*, Conceptual Modeling Perspectives, Springer International Publishing, pp. 231–245.

Liu, Z., Jiang, B., & Heer, J. (2013). imMens : Real-time Visual Querying of Big Data. In: *Eurographics Conference on Visualization*, Blackwell Publishing, Vol. 32, Number 3.

Lokhorst, C., & Wulfse, B.J. (2015). Chain cooperation as a critical success factor in Smart Dairy Farming. In: *Proceedings of the 7th European Conference on Precision Livestock Farming,* Precision Livestock Farming '15, pp. 643–650.

Rutten, C.J., Velthuis, A.G.J., Steeneveld, W., & Hogeveen, H. (2013). Invited review: Sensors to support health management on dairy farms. *Journal of Dairy Science*, *96*(4): 1928–1952.

Tilkov, S., & Verivue, S.V. (2010). Node . js : Using JavaScript to Build High-Performance Network Programs. *IEEE Computer Society*, *14*(6): 80–83.

Vavilapalli, V.K., Murthy, A.C., Douglas, C., Agarwal, S., Konar, M., Evans, R., Graves, T., Lowe, J., Shah, H., Seth, S., Saha, B., Curino, C. O'Malley, O., Radia, S., Reed, B., Baldeschwieler, E. (2013). Apache hadoop yarn: Yet another resource negotiator. In: *Proceedings of the 4th annual Symposium on Cloud Computing,* pp. 5.

Vonder, M.R., Van Der Waaij, B.D., Harmsma, E.J., & Donker, G. (2015). Near real-time large scale (sensor) data provisioning for PLF. In: *7th European Conference on Precision Livestock Farming,* Precision Livestock Farming '15, pp. 290–297.

Wang, L., Wang, G., & Alexander, C.A. (2015). Big Data and Visualization: Methods, Challenges and Technology Progress. *Digital Technologies*, *1*(1): 33–38.

Zaharia, M., Xin, R.S., Wendell, P., Das, T., Armbrust, M., Dave, A., Meng, X., Rosen, J., Venkataraman, S., Franklin, M.J., Ghodsi, A., Gonzalez, J., Shenker, S., Stoica, I. (2016). Apache Spark: A Unified Engine For Big Data Processing. *Communications of the ACM*, *59*(11): 56–65.

Modelling restricted feeding conditions on cows' feeding behaviour on pasture-based milk production systems to develop a Decision Support System

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Abstract

The aim of this study was to identify a set of feeding behaviour and activity related variables that could potentially detect a shortage of available feed for the individual cow on pasture. A group of lactating cows was offered 100% of their intake capacity as herbage allowance throughout a 10-week experimental period, while another group was offered 60% of their intake allowance, either for a two week or six week period in springtime. Each cow was equipped with an automated noseband sensor. The data were analysed by using a binomial generalized lineal model (GLM). The GLM was examined for the classification of full or restricted herbage allowance as a function of a previously identified set of characteristics. The model was further refined by including additional characteristics, which achieved higher prediction performance. For the combined data, the refined model achieved 77% accuracy, 75% sensitivity, 78% specificity and F-score 0.76 towards a decision support system for grass utilisation in pasture based milk production.

Keywords: feeding behaviour, generalized linear model, classification performance

Introduction

In precision dairy farming, one of the key factors for farmers to recognise biosensor technologies is the scope of utilising biosensor data to develop a reliable pasture-based grazing system (French *et al.*, 2015). In this context, the current study aims to identify a set of feeding behaviour and activity related characteristics of milking cows recorded by the RumiWatchSystem (Alsaaod *et al.*, 2015) and quantify their relationship with insufficient grass allowance, so that the study findings can be further used as guidance for developing a decision support system. The efficacy of such a support system depends mainly on its ability to identify the correct grass allowance per cow. This study, therefore, considered the association between grazing behaviour and activity with grass allowance as means of identifying one of the groups for grazing cows: access to sufficient or insufficient grass.

Werner *et al.* (2019) suggested that bite frequency (BITEFREQ), rumination time per day (RUMINATETIME), rumination chews per bolus (RUMICHEWBOLUS) and frequency of standing or laying (STANDLAY) were significantly affected by restricted grass allowance. Therefore, this study first considered only these variables to examine their predictive performance using a GLM with logit link, i.e. logistic regression (LR) model. The model was further refined by incorporating additional characteristics using a stepwise method (Efroymson, 1960). Thus, a refined set of feeding behaviour and activity related variables was proposed for which the LR model increased the classification performance indices.

Material and methods

Data collection and cleaning

Data for this study came from a larger overall experiment at Teagasc, Moorepark Dairy Research Farm, Animal & Grassland Research and Innovation Centre, Fermoy, Co.

Cork, Ireland (Claffey, 2018). The experiment was conducted in springtime using 105 calving cows to examine the effects of restricted pasture allowance on milk production, immunology and indicators of reproductive health of grazing dairy cows. Ethical approval was received from Teagasc Animal Ethics Committee (TAEC; TAEC100/2015) and procedure authorisation was granted by the Irish Health Products Regulatory Authority (HPRA).

For the current study, 40 focal cows were selected for recording the feeding behaviour and activities using the RumiWatch System. Out of these, 10 cows were randomly assigned to a group where cows were offered 100% of their intake allowance and the remaining 30 cows were assigned to the restricted allowance groups where cows were offered 60% of their intake allowance. The 60% group was further divided into six sub-groups based on the duration of restriction, i.e. two-week (2) or six-week (6) period and three time points of (early) lactation at the commencement of restricted allowance: *start* (S: restriction starts at the beginning of experiment), *mid* (M: two weeks after the S restriction commenced) or *late* (L: four weeks after the S restriction commenced). The behaviour of the cows in the 100% group was monitored over 10-week period. The three cow groups on the two-week restricted pasture allowance (PA) had their behaviour recoded during the full two-week periods whereas the behaviour of the three groups on the six-weeks restricted PA was recorded during the last two-week period due to limited sensor device resources (Werner *et al.*, 2019). Throughout this paper, the notions S2, M2, L2, S6, M6 and L6 denote the six treatment sub-groups as well as the subsets of combined data, which included the records of the respective cows from the insufficient and sufficient grass allowance groups.

In total 1,221 records were collected during the experimental period. For the safety and strictness, all records with missing values were removed. The combined data included 629 records for cows that had 100% intake allowance and 592 records for cows with 60% of the intake allowance. However, the subsets of the combined data S2, M2, L2, S6, M6 and L6 were unbalanced.

Research design

The research design comprised three parts for this study. The first part was data exploring, and fitting univariate logistic regression models with one exposure variable at a time. At this stage, all the feeding and activity related variables recorded by the RumiWatch System were considered for screening. Based on the results of univariate analyses, a set of nine candidate variables was selected for further analysis using multivariate models.

The candidate set identified in the first part included the four previously identified characteristics (Werner *et al.*, 2019). These variables were used in Model 1 as follows.

$$\log\left(\frac{\pi_i}{1-\pi_i}\right)=\beta_0+\beta_1 BITEFREQ_i + \beta_2 RUMINATETIME_i + \beta_3 RUMICHEWBOLUS_i + \beta_4 STANDLAY_i \quad (1)$$

The second part was data classifications using Model 1. Given the recorded values of the predictor variables, the fitted model estimates the log of odds, $\log\left(\frac{\pi_i}{1-\pi_i}\right)$ where π_i=P(Y=1), i.e. the probability that the cow had insufficient (60%) PA and $(1-\pi_i)$=P(Y=0) i.e. the probability that it had sufficient (100%) PA. The regression coefficients β's are the instantaneous change in *log(odds)* for one unit change of the independent variable, holding all other variables constant (Kabacoff, 2015). For each data set, the estimated coefficients of *Model 1* were exponentiated to obtain *odds ratio* (*OR*) which described the relationship between each characteristic and the odds of insufficient grass allowance in a multivariate framework.

The third part of the study was model refinement based on stepwise regression. The procedure identified the best set of characteristics from the nine candidates for which the exploratory analysis showed significant association with the pasture allowance groups. Thus, a refined classification model was proposed. The classification performance of Model

1 and the refined models was compared based on accuracy, sensitivity, specificity, and F-score. These indices were estimated form the cross validation study as follows. Given data, a random sampling divided the rows into a training set and a testing set such that each row had 70% chance of being included in the training set and 30% chance of being included in the testing set. Both the models were estimated from the training set and applied to classify the grass allowance for each cow in the testing set. Based on the true and predicted classes, a confusion matrix was created for estimating the classification indices. The procedure was repeated 1,000 times and the indices were summarised by the means. The statistical analyses were performed by using *glm, step, acf* (R core Team, 2019) and *lrm* (Frank & Harrell, 2019) functions and the codes for repeated cross validations were written in R3.5.3.

Results and discussion

Estimation of Model 1

Table 1 presents the estimated coefficients of Model 1 and the odds ratios (in brackets) for the subsets and combined data. While the results for combined data demonstrate that each characteristic was significantly associated with the odds of insufficient grass allowance, separate analyses show that the magnitude of effects were different for different duration of restriction and the stages of lactation. For example, using S2, the odds of insufficient grass was expected to increase by a factor of 1.2 for every unit increase in the 'bite-frequency' (holding other characteristics fixed). The remaining variables had insignificant negative effects on the odds.

Table 1. Estimated coefficients with odds ratios (in brackets) for Model 1 based on the subsets and combined data

Variables	S2	M2	L2	S6	M6	L6	Combined
BITEFREQ	0.18*** (1.20)	0.083** (1.09)	0.09* (1.09)	0.105*** (1.11)	0.177*** (1.19)	0.094** (1.09)	0.12*** (1.12)
RUMINATETIME	-0.003 (0.99)	-0.012*** (0.99)	-0.012*** (0.99)	-0.012** (0.99)	-0.009*** (0.99)	-0.009*** (0.99)	-0.008*** (0.99)
RUMICHEWBOLUS	-0.039 (0.96)	-0.006 (0.99)	-0.135** (0.87)	-0.317*** (0.73)	-0.109** (0.90)	-0.14** (0.87)	-0.12*** (0.89)
STANDLAY	-0.17*** (0.84)	-0.25*** (0.78)	-0.086 (0.92)	-0.056 (0.95)	-0.122*** (0.88)	-0.05 (0.95)	-0.107*** (0.87)

P-value: *** < 0.001; ** < 0.01; * < 0.05

However, the magnitude of the effects and corresponding *P-values* for significance tests were different across the data sets, though the direction of effects was the same in all cases. One possible reason for the differences in results is that the combined data were obtained from the six blocks of cows that were attributed to different level combinations of restriction period and lactation stage factors. This implies that the between group variation of each characteristics among the treatment cows was not assumed to be equal. As a result, Model 1 did not fit all data sets equally well. For example, the pseudo R^2 for S2 (R^2=0.62), M2 (R^2=0.51), L2 (R^2=0.62), S6 (R^2=0.87), M6 (R^2=0.47), L6 (R^2=0.43) and the combined data (R^2=0.54) reveal that Model 1 best explained the percent of variation in *log (odds)* for S6 group. Comparing S2 and S6 this is reasonable since intuitively, cows with longer periods of insufficient feed intake are expected to show relatively greater difference in certain behavioural characteristics

from the control cows than those with shorter period of insufficient feed intake. Based on this assumption, given lactation stage, it was expected that the pseudo would be higher for six-week restriction data than two-week restriction data. However, Model 1 achieved lower pseudo R^2 for six-week restriction for both M and L groups.

Table 2. Estimated coefficients with odds ratios (in brackets) for the refined models based on the subsets and combined data

Variables	S2	M2	L2	S6	M6	L6	Combined
BITEFREQ	0.20*** (1.22)	0.124*** (1.13)	0.237*** (1.27)	.301*** (1.35)	0.303*** (1.35)	0.514*** (1.67)	0.13*** (1.14)
RUMINATETIME	0.004 (1.004)	-0.009** (0.99)	-0.007* (0.99)	-0.004 (0.99)	0.002 (1.00)	-0.007 (0.99)	-0.002 (0.99)
RUMICHEWBOLUS	0.131* (1.14)	0.105 (1.10)	-0.029 (0.97)	-0.204** (0.82)	-0.047 (0.95)	0.158** (1.17)	-0.064*** (0.94)
STANDLAY	-0.14** (0.87)	-0.271*** (0.76)	-0.093 (0.91)	-0.134* (0.87)	-0.154*** (0.86)	-0.153** (0.86)	-0.12*** (0.89)
CHEWPBOLUS	-0.353*** (0.70)	-0.118* (0.88)	-0.325*** (0.72)	-0.312*** (0.73)	-0.136** (0.87)	-0.595*** (0.55)	-0.14*** (0.87)
RUMIBOUTLENGTH	-0.091* (0.91)	-0.090* (0.91)	-0.074* (0.93)	-0.126** (0.88)	-0.17*** (0.84)	-0.109** (0.90)	-0.084*** (0.92)
HACTIVITY.mean	0.031* (1.03)	-0.007 (0.99)	-0.012 (0.99)	-0.019 (0.98)	-0.0002 (0.99)	0.052** (1.05)	0.013*** (1.01)

P-value: *** < 0.001; ** < 0.01; * < 0.05

Model refinement

Apart from the four characteristics in Werner *et al.* (2019), the exploratory analysis of this study identified the candidate variables: number of rumination chews per day (RUMINATECHEW), number of bolus per day (BOLUS), number of chews per bolus (CHEWPBOLUS), mean rumination bout length per day (RUMIBOULENTH) and number of head activities (up or down) per hour of the day (HACTIVITY.mean). In order to increase the goodness of fit (and classification performance), Model 1 was refined by using the additional variables.

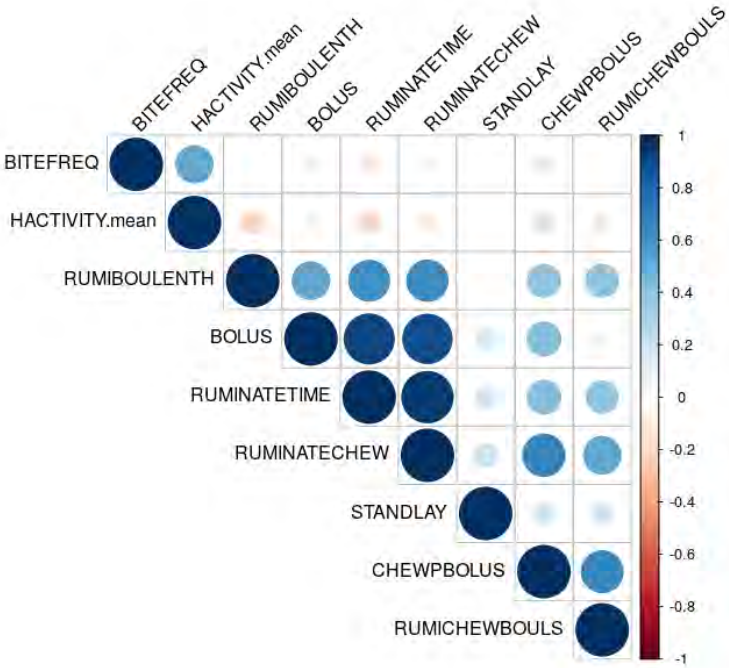

Figure 1. Correlation plots among the feeding behaviour and activity related variables

However, based on the combined data, the correlation plots in Figure 1 indicate that there would be a concern with GLM using all (nine) variables since some of the variables were highly collinear. As a result, a sequential strategy, i.e. stepwise procedure was adapted, through which the less significant variables were trimmed using backward search direction. Similarly, a refined set of characteristics was obtained by applying the stepwise regression to S2, M2, L2, S6, M6 and L6 data sets. Table 2 presents the estimated coefficients and the odds ratios for the refined models. The estimated effects of the common characteristics were slightly different from Model 1. For example, unlike Model 1 the effect of 'rumination, time' was insignificant in most cases. Also, using the combined data, the OR of 'bite frequency', 'rumination chews per bolus' and 'standing or laying frequency' in the refined model were slightly higher than Model 1. In all cases, bite-frequency had strong positive relationship and chews per bolus and rumination bout length had negative relationship with the odds of insufficient grass allowance. Conversely, rumination time had significant negative effect for S2 and M2 and rumination chew per bolus had significant negative effects for S6 and L6 data sets. Head activity per hour had a small effect and the relationship was significant for S2, S6 and combined data. The effect of standing or laying frequency was highly significant for all cases except L2.

Table 2 further reveals that unlike Model 1, for each lactation stage the OR of bite frequency was relatively higher for six-week restriction period than two-week restriction period. Similarly, the effects of rumination bought length and chews per bolus had negative effects across the subsets and combined data. The pseudo R^2 of S2 (R^2=0.66), M2 (R^2=0.57), L2 (R^2=0.62), S6 (R^2=0.90), M6 (R^2=0.61) and L6 (R^2=0.80) and combined data (R^2=0.60) clearly indicate that the refined model achieved higher explanatory power than Model 1 in all cases. Moreover, unlike Model 1, the refined model achieved higher explanatory power for

M6 than M2 and L6 than L2. Thus, the refined model validates the assumption that the characteristics could explain the variation in *log(odds)* better for longer period of restricted PA than shorter period. Thus, the refined model should be preferred to Model 1.

Classification performance

In this section, the predictive performance of Model 1 and the refined models was compared separately for S2, M2, L2, S6, M6, L6 and combined data. In each case, the performance was evaluated based on accuracy, sensitivity, specificity, and F-score. Table 3 presents the estimates of these indices based on the cross validation study.

Clearly, the refined models performed better than Model 1 with respect to all indices. In addition, the restriction period affected the predictive performances. Accuracy is a popular performance measure of classifiers, since it reflects the overall prediction performance. Given lactation stage, estimated accuracy was higher for six-week restriction data than two-week restriction data.

For example, Model 1 achieved 77% accuracy for S2 and 84% accuracy for S6 data. The corresponding figures for the refined model are 80% and 88%, respectively. This implies that in general cows were more apt to be correctly classified in case of longer duration of insufficient feed allowance.

Table 3. Performance of Model 1 and the refined models based on cross validation study

Models	Indices	S2	M2	L2	S6	M6	L6	Combined
Model 1	Accuracy	0.77	0.79	0.75	0.83	0.79	0.84	0.73
	Sensitivity	0.62	0.63	0.48	0.72	0.45	0.33	0.74
	Specificity	0.85	0.88	0.87	0.89	0.91	0.95	0.73
	F-score	0.64	0.67	0.52	0.73	0.49	0.44	0.73
Refined model	Accuracy	0.80	0.82	0.80	0.87	0.81	0.88	0.77
	Sensitivity	0.68	0.70	0.61	0.80	0.54	0.63	0.75
	Specificity	0.88	0.88	0.88	0.91	0.91	0.94	0.78
	F-score	0.70	0.71	0.64	0.81	0.58	0.64	0.76

Since the data were unbalanced, further comparisons based on sensitivity and specificity scores suggest that for L6 Model 1 achieved 84% accuracy due to high specificity *(0.95)*. Here, specificity refers to the proportion of 100% intake allowances that were correctly predicted. However, in this case the rate of correct classification of insufficient grass allowance was not reliable due to very low sensitivity *(0.33)*. Conversely, the refined model, in this case achieved 60% sensitivity while maintaining specificity at the high level (0.94). The refined model had a concern of lower sensitivity (0.54) for M6 data, though the estimate was relatively higher than Model 1 (0.45). For the combined data, both models maintained a good balance in all indices while refined model having higher scores than Model 1.

Since the current study aimed to contribute to the development of a pasture-based decision support system, identifying insufficient grass allowance may be often more important than full intake allowance. In such cases, the F-score is a better performance measure

since it maintains a balance between the precision (proportion of predicted insufficient allowance that were actually insufficient) and sensitivity of the classifiers. As with other indices, the F-score of the refined models was higher than Model 1 in all cases. However, the low sensitivity resulted low F-score for M6. Future studies need to address this issue and focus on further improvement of the classification models.

Conclusion

This study explored the performance of a set of previously identified feeding behaviour and activity related variables and refined the set in the context of classification. Seven characteristics of lactating spring cows were identified which were significantly associated with the odds of insufficient grass allowance. No unique set of characteristics was found to be the best indicators for all cases. The model adequacy and prediction performance depended on the duration of insufficient feeding: in general, cows with longer period of insufficient allowance were more apt to be correctly identified than those with shorter restriction period. The results of Table 2 can be used as guidance for heuristic estimation of the likelihood of insufficient grass allowance, given that other factors are similar to the underlying experimental conditions. However, since the sensitivity of the refined model was still less than 0.8 in most cases, care should be taken while using the models for future prediction. Further study should address this issue and also focus on thresholding the important characteristics towards developing a decision support system.

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References

Alsaaod, M., Niederhauser, J.J., Beer, G., Zehner, N., Schuepbach-Regula, G., and Steiner, A. (2015). Development and validation of a novel pedometer algorithm to quantify extended characteristics of the locomotor behaviour of dairy cows. *Journal of Dairy Science*, 98(9): 6236–6242.

Claffey, A., Delaby, L., Lewis, E., Boland, T.M., and Kennedy, E. (2018). Pasture allowance, duration and lactation stage: effects on early lactation production. In: Proceedings 27. *General Meeting of the European Grassland Federation (EGF) (Vol. 23, p. np) Wageningen Academic Publishers.*

Efroymson, M.A. (1960). Multiple regression analysis. Mathematical Methods for Digital Computers, John Wiley & Sons, New York.

Frank, E., Harrell, Jr. (2019). rms: Regression Modelling Strategies. R package version 5.1–5.3.

French, P., O´Brien, B., Shalloo, L. (2015). Development and adoption of new technologies to increase the efficiency and sustainability of pasture-based systems. *Animal Production Science,* 55: 931–935.

Kabacoff, R. (2014). R in Action: Data Analysis and Graphics with R. Manning.

Nagelkerke, N. (1991). A note on a general definition of the coefficient of determination. *Biometrika,* 78(3): 691–692.

R Core Team (2019). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Viena, Austria.

Werner, J., Umstatter, C., Kennedy, E., Grant, J., Leso, L., Geoghegan, A., Shaloo, L., Schick, M., and O'Brian, B. (2019). Identification of possible cow grazing behaviour indicators for restricted grass availability in a pasture-based spring calving dairy system. *Livestock Science,* 220: 74–82.

Impact of broiler behaviour on key production indices

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Abstract

A camera-based PLF monitoring system can be used to identify deviations in broiler flock behaviour at an early stage. The goal of this research is to identify management issues in the house and relate the outcome of a camera-based monitoring system for bird behaviour to key production indices. Three commercial broiler farms in Belgium were equipped with the eYeNamicTM camera-based monitoring system. The build-in image analysis software analyses automatically the flock behaviour by calculating indices for activity, occupation density and distribution of the broilers in the house. Feed Conversion Rate (FCR), Water-Feed Ratio (WFR) and Average Daily Growth Rate (ADGR) were calculated using production data extracted from the available controller units for 14 flocks. Between Sep 2017 and Sep 2018, several cases affecting bird behaviour were found. Deviations in behaviour were automatically identified by an early warning algorithm analysing the recorded activity, occupation and distribution indices. The Time Out Of Comfort (TOOC) was defined as the cumulative sum of these deviations per round. The correlation r between FCR and TOOC was 0.692. Per hour out of comfort, the feed conversion rate increased with 0.0069. Per hour out of comfort, the water-feed ratio decreased with 0.0050 (r = -0.537). Per hour out of comfort, average daily growth rate decreased with 0.1786 gram (r = -0.513). In conclusion, it was demonstrated that a continuous observation of flock behaviour allows the farmer to solve management issues as quickly as possible, which will improve the technical and economical key production indices on his farm.

Keywords: image analysis, activity, occupation, distribution, poultry, precision livestock farming

Introduction

Worldwide the demand for animal products keeps on rising, a 70% increase is predicted by 2050 (FAO, 2013). Yearly, already more than 65 billion chickens are slaughtered (FAOSTAT, 2018). To produce this amount of animals, farming methods have shifted from extensive to intensive. Broilers are today typically housed with thousands together in commercial environments making it impossible for the stakeholders to monitor all animals individual and accurate.

Precision Livestock Farming (PLF) gives an answer to these problems by monitoring the animals automatically, continuously and in real-time to help the farmer to take management decisions based on objective measured parameters (Norton & Berckmans, 2018). Camera technology have the advantage that they can measure the animals without imposing additional stress. Previous studies show that cameras can be used to observe weight (De Wet *et al.*, 2003; Mortensen *et al.*, 2016), broiler welfare (Dawkens *et al.*, 2012, 2013), and lameness (Aydin *et al.*, 2010, 2017; Silvera *et al.*, 2017; Van Hertem *et al.*, 2018). Kashiha *et al.* (2013) show that deviations from activity and distribution can be used as an early warning monitoring system.

The objective in this study is to identify issues/problems in the broiler house based on behavioural changes of the broilers monitored by a camera system and relate the time spend during these moments to key performance indices. The total TOOC from the activity, distribution and occupation is related to the FCR, WFR, ADGR.

Material and methods

Experimental data

Data were gathered on three commercial broiler farms in Belgium (Table 1). Water supply, feed supply and animal growth were automatically registered by the available control units in the farm (Fancom B.V., the Netherlands), and the data were sampled every hour and exported to a csv-file on the local farm computer. The number of dead birds and culled birds per round was on a daily basis manually entered in the farm control units by the farm personnel. The total number of dead birds over the total number of birds entering the house accounted for the flock mortality. Bird mass was automatically registered by a weighing control unit with weighing platforms in the house (Fancom B.V., the Netherlands). These data were sampled every hour from the control unit and exported to a csv-file on the local farm computer.

In total, there were 19 fattening rounds of broilers in this period, but due to power outages during the fattening rounds, or corrupt data registration in the farm computer, the data of five fattening rounds were not available for analysis. For data analysis, 14 complete fattening rounds were used.

Table 1. Overview of farm specifications

	Farm A	Farm B	Farm C
Floor area	2,400 m^2	1,476 m^2	1,280 m^2
Max. number of birds	52,000	32,000	28,000
Number of feeder lines	5	4	4
Number of drinker lines	6	6	5

Key Production Indices were calculated from the gathered farm data. The length of the fattening period (FP) was determined from the brooding day until the house was cleared from all birds. Water Feed Ratio (WFR) was calculated as the ratio of water and feed supply of the fattening round at the end of the fattening period. Average Daily Growth Rate (ADGR) was calculated from the from the brooding weight of the animals, the end weight of the birds at clearance and the length of the fattening period.

The broiler houses were equipped with a camera-based monitoring system for bird behaviour analysis (eYeNamic™, Fancom B.V., the Netherlands). The system consisted of four cameras that were installed in top down perspective from the house ceiling, approx. at a height of 4 m. The cameras were installed in a $2x^2$ grid in the house at 1/3 and 2/3 of the length of the house, and at 1/3 and 2/3 of the width of the house. In this layout, the cameras were covering a substantial part of the floor area in the width of the house. Each camera covered a 4 m by 10 m area of the floor space. It was advised to cover all water and drinker lines in the field of view of the cameras. The system automatically translated the recorded images into data on bird activity levels, bird occupation density levels in the image and bird distribution in the house. These data were sampled every minute by the farm management software program on the local farm computer, and per camera unit stored into a csv-file. For the data analysis, the data per camera unit were aggregated on house level resulting in the average activity level of the birds in the house per minute, the average occupation density of birds in the house per minute and the distribution index of birds in the house.

Extraction time out of comfort

An early warning algorithm was developed and tested in this experiment. The early warning algorithm used the average value in the last 48 hours as the norm, and the average value in the last 24 hours as the signal. The limits for normal behaviour were calculated from the norm values and the standard deviation of the value in the last 24 hours. When the signal was out of the limits for normal behaviour, bird behaviour was considered to be out of comfort. This procedure was done on all three eyenamic variables (activity, occupation and distribution) and with a sliding window procedure of 24 hours that was being updated every minute. In the analysis for this work, the total number of minutes out of comfort were aggregated per fattening round, and these data are presented in the results section and in Table 2.

Results and Discussion

For every individual production round in the experiment the total TOOC was calculated (Table 2). For the seven production cycles in farm A, this time ranged between 1,777 minutes and 3,314 minutes (29.6 h and 55.2 h). Farm B (5 production cycles) showed more variation with a minimum TOOC of 955 minutes (15.9 h) and a maximum of 3,474 minutes (57.9 h). Farm C, only two production cycles, relative to the other farms a TOOC with 3,193 minutes (53.2 h) and 4,168 minutes (69.5 h).

Table 2. Overview of the key production data in the three broiler farms gathered during the experimental period

Farm	TOOC	WFR	FCR	FP	ADGR	mortality
A	2,239	1.76	1.63	42	57.9	2.14
A	3,314	1.76	1.54	42	62.8	1.55
A	2,465	1.74	1.56	42	60.8	3.18
A	2,309	1.75	1.57	42	60.9	1.70
A	1,777	1.92	1.64	42	58.1	4.03
A	1,798	1.99	1.57	44	57.2	2.58
A	2,109	1.88	1.62	43	56.5	1.99
B	3,474	1.51	1.84	43	53.3	2.63
B	2,048	1.63	1.43	40	64.3	3.83
B	955	1.67	1.47	40	63.9	3.38
B	1,294	1.75	1.47	42	61.2	2.13
B	1,952	1.67	1.51	41	58.9	2.70
C	3,193	1.60	1.83	43	48.7	3.57
C	4,168	1.53	NA	43	NA	3.79

TOOC = Time Out of Comfort [minutes]; WFR = Water-Feed Ratio [-]; FCR = Feed Conversion Rate [-]; FP = Fattening Period [days]; ADGR = Average Daily Growth Rate [grams]

All production cycles ranged between 40–43 days. The WFR ranges from 1.51–1.99 and is higher in farm A than in farm B and C. The FCR ranged between 1.43–1.84, except for an outlier of 1.84 farm B shows the lowest FCR. The ADGR was the lowest in farm C, 48.7 grams, and the maximum was 64.3 grams measured in farm B. Mortality ranges from 1.55–4.03. More details can be seen in Table 2.

This work is an attempt to relate key production indices to the TOOC independent from other factors such as broiler quality, farm, and feed diet. Figure 1 shows the positive relation between the FCR and the TOOC. A positive correlation (Table 3) of 0.692 is calculated between both variables. Indicating that if the birds spend more TOOC, the birds have a higher FCR, more feed is needed to grow the birds. Per hour out of comfort the FCR increases with 0.0069. Hence, the eYeNamic system can give an indication of the FCR ratio. The best fit linear regression model is $FCR = 1.16 \cdot 10^{-4}\ TOOC + 1.33$ ($R^2 = 0.479$).

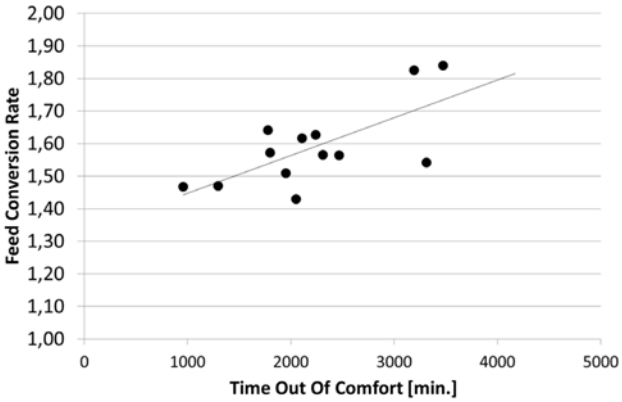

Figure 1. Graphical overview of the linear relation between time out of comfort and Feed Conversion Rate

Table 3. Correlation coefficient of the three selected production indices in relation to Time Out of Comfort and the hourly incremental values

	WFR	FCR	ADGR
Correlation coefficient	-0.537	0.692	-0.513
Hourly increment	-0.0050	0.0069	-0.1786

Figure 2 shows a negative relation between the WFR and the TOOC. A negative correlation of -0.537 (Table 3) is calculated and per hour out of comfort the WFR decreases with 0.0050. The best fit linear regression model is $WFR = -8.33 \cdot 10^{-5}\ TOOC + 1.92$ ($R^2 = 0.289$).

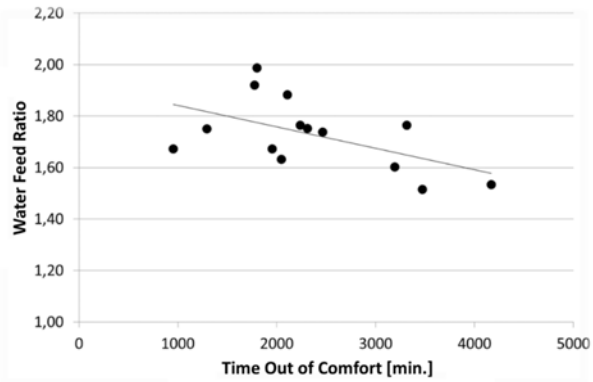

Figure 2. Graphical overview of the linear relation between time out of comfort and Water Feed Ratio

In Figure 3 a negative relation between the ADGR and the TOOC is shown. Indicating that the more time the animals spend out of comfort the lower the growth. A correlation of -0.513 (Table 3) is calculated and for every hour out of comfort a decrease of 0.1786 grams in growth is calculated. The best fit linear regression model is $ADGR = -2.98 \cdot 10^{-3}\ TOOC + 65.4$ ($R^2 = 0.263$).

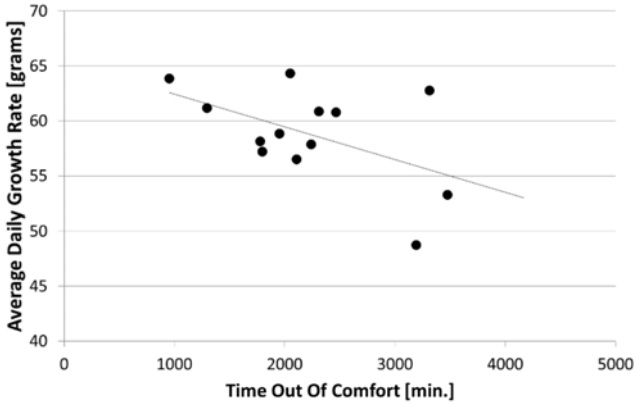

Figure 3. Graphical overview of the linear relation between time out of comfort and Average Daily Growth Rate

Conclusions

Data are gathered from commercial broiler farms. Out of the total 19 fattening rounds in the observation period, only 14 fattening rounds (74%) resulted in complete data. Data analysis shows that the correlation r between FCR and TOOC is 0.692. Per hour out of comfort, the feed conversion rate increases with 0.0069. Per hour out of comfort, the water-feed ratio decreases with 0.0050 (r = -0.537). Per hour out of comfort, average daily growth rate decreases with 0.1786 gram (r = -0.513). These results demonstrate that a continuous observation of flock behaviour allows the farmer to solve management issues as quickly as possible, which will improve the technical and economical key production indices on his farm.

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References

Aydin, A., Cangar, O., Eren Ozcan, S., Bahr, C., Berckmans, D. (2010). Application of a fully automatic analysis tool to assess the activity of broiler chickens with different gait scores. *Computers and Electronics in Agriculture* 73, 194–199.

Aydin, A. (2017). Development of an early detection system for lameness of broilers using computer vision. *Computers and Electronics in Agriculture* 136, 140–146.

Dawkins, M.S., Russell, C., Roberts, S.J. (2012). Optical Flow, flock behaviour and chicken welfare. *Animal Behaviour* 84: 219–223.

Dawkins, M.S., Russell, C., Merelie, K., Roberts, S.J. (2013). In search of the behavioural correlates of optical flow patterns in the automated assessment of broiler chicken welfare. *Applied Animal Behaviour Science* 145: 44–50.

De Wet, L. Vranken, E. Chedad, A., Aerts, J.M., Ceunen, J., Berckmans, D. (2003). Computer assisted image analysis to quantify daily growth rates of broilers chickens. *British Poultry Science* 44(4): 449–457.

FAO (Food and Agricultural Organization). (2013). Poultry Development Review. Rome.

FAOSTAT. (2018). http://www.fao.org/faostat/en/#data/QL. Area: world; item: meat,chicken; Element: Producing Animals/Slaughtered. Accessed on 3/7/2018.

Mortensen, A.K., Lisouski, P., Ahrendt, P. (2016). Weight prediction of broiler chickens using 3D computer vision. *Computers and Electronics in Agriculture* 123, 319–326.

Norton, T., Berckmans, D. (2018). Engineering advances in Precision Livestock Farming. *Biosystems Engineering* 173, 1–3.

Silvera, A.M., Knowles, T.G., Butterworth, A., Berckmans, D., Vranken, E., Blokhuis, H.J. (2017). Lameness assessment with automatic monitoring of activity in commercial broiler flocks. *Poultry Science* 96(7): 2013–2017.

Van Hertem, T., Norton, T., Berckmans, D., Vranken, E. (2018). Predicting broiler gait scores from activity monitoring and flock data. *Biosystems Engineering* 173, 93–102.

Evaluating rumen temperature during the pre-slaughter phase as a predictor for meat quality

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Abstract

The pre-slaughter phase involves a number of stress inducing situations including transportation, exposure to a novel environment and mixing; an outcome of which can have a detrimental effect on meat quality. The occurrence of dark, firm, dry (DFD) beef results in substantial economic losses for the red meat industry. Stress-induced hyperthermia is a well-documented physiological response to stressful events and may provide an indication as to which cattle are at risk of producing DFD meat. However, the continuous, non-invasive monitoring of core body temperature has not always been practical. This is now changing through the development of new technologies, such as rumen temperature boluses. Thus, the objective of this study was to investigate the relationship between pre-slaughter phase rumen temperature, existing haematological welfare indicators and instrumental meat quality. This study involved 40 Holstein bulls (15.8 ± 0.08 months of age; 575.9 ± 8.84kg live weight) which had a rumen temperature bolus (Thermobolus, Medria) administered, to record rumen temperature at five minute intervals. Bulls were transported 26 miles (42 km) to a commercial abattoir. During the pre-slaughter phase rumen temperature, cortisol, CK, and LDH all rose significantly ($P < 0.001$), in comparison to that recorded during the basal period. Bulls with a greater pH_{ult} had a significantly greater ($P < 0.001$) maximum rumen temperature during lairage. Instrumental meat quality was strongly associated with pre-slaughter rumen temperature and cortisol and CK concentrations at slaughter. Therefore, pre-slaughter phase rumen temperature may have the potential to act as a predictor for meat quality.

Keywords: Stress-induced hyperthermia, ultimate pH, rumen temperature bolus

Introduction

Meat colour is the primary means by which consumers assess meat quality and therefore has a profound impact on consumer purchasing decisions (Ponnampalam *et al.*, 2013). Furthermore, dark cutting meat is associated with increased toughness together with a reduced shelf-life and flavour (Ponnampalam *et al.*, 2017). Dark cutting meat still remains a problem, with incidence rates in Great Britain reported at 8.8% (Warriss and Brown, 2008) thus, resulting in a significant cost to the red meat industry (Teke *et al.*, 2014). Meat quality characteristics (ultimate pH (pH_{ult}), tenderness, colour and water holding capacity) are determined by the rate at which muscle acidifies post-mortem (Tarrant and Lacourt, 1984). Anaerobic glycolysis is the process by which muscle glycogen stores are utilised to produce lactic acid, which in turn, reduces post-mortem muscle pH to optimum levels. Where muscle glycogen stores are insufficient, pH will remain high (> 5.8) (Lister, 1988). The depletion of muscle and liver glycogen stores is widely known to occur in response to stress (Losada-Espinosa *et al.*, 2018), due to glycogenesis following the activation of the sympathetic nervous system (Ponnampalam *et al.*, 2017). The routine components of the pre-slaughter phase (transport, mixing and exposure to an unfamiliar environment and personnel) will each present a stress risk (Ferguson & Warner, 2008). Thus, good management during the pre-slaughter is vital to ensure stress is kept to a minimum and meat quality is not negatively impacted.

A stress response is comprised of a number of physiological and haematological changes, one of which is a short-term elevation in core body temperature, known as stress-induced hyperthermia (Proctor & Carder, 2015). The most widely researched haematological change is the secretion of stress hormones such as cortisol (Burdick *et al.*, 2010). In addition, muscle enzymes such as creatine kinase (CK) and lactate dehydrogenase (LDH) are released into the serum following vigorous exercise and muscle damage (Chulayo & Muchenje, 2017). Many of these physiological changes are considered reliable measures of animal welfare, however, the potential for these indicators to be used as predictors of meat quality has been overlooked. This is primarily due to the fact that sampling methods can be invasive, time-consuming and expensive. Furthermore, data is often discontinuous, or not available in real-time. However, rumen temperature boluses are a new technology that offer continuous, non-invasive data collection.

Materials and methods

Animal management and experimental design

This study was undertaken at AFBI, Hillsborough in June 2018 and consisted of 40 Holstein bulls of 15.8 ± 0.08 months of age and 575.9 ± 8.84kg live weight. Bulls were fed an *ad libitum* diet compromised of grass silage (871 g kg^{-1} dry matter (DM), 124 g $kgDM^{-1}$ crude protein (CP) and 10.6 MJ $kgDM^{-1}$ metabolisable energy (ME) and concentrates (150 g $kgDM^{-1}$ CP and 11.1 MJ $kgDM^{-1}$ ME). Bulls were housed on slatted accommodation in groups of 3.1±0.12 bulls before being transported to a commercial abattoir in a naturally ventilated, double decker lorry. The lorry consisted of eight pens and bulls were transported in a mean group size of 5.48±0.156 bulls at a space allowance of 1.53m^2. Journey time, time waiting to unload, and lairage duration were recorded for each animal. The bulls were slaughtered using the commercial abattoir procedure and the time of stunning was recorded for each animal.

Rumen temperature

Each bull had a rumen temperature bolus (ThermoBolus Small, Medria, France) administered which automatically recorded rumen temperature to a tenth of a degree Celsius at five minute intervals. The 48 hours prior to the onset of loading was considered as the basal period. Rumen temperature during transportation and lairage consisted of the durations between loading and unloading; and between unloading and slaughter, respectively. For each of these three durations, a mean and maximum rumen temperature were calculated.

Blood collection and haematological variables

Bulls were blood sampled at three time points; 24 hours prior to transport (T1), 0 hours prior to transport (T2) and at slaughter (T3). The mean of T1 and T2 was considered as an individual basal value. T1 and T2 were obtained via tail venipuncture while T3 was taken from the jugular vein during exsanguination. Blood (10ml) was collected into evacuated tubes (with no additive) at each time point for determination of cortisol, creatine kinase (CK) and lactate dehydrogenase (LDH). Blood samples were stored at 4 °C prior to being centrifuged at 3,000 rpm at 4 °C for 20 minutes. Plasma was collected from each sample and stored at -20 °C until analysis was conducted by NationWide Laboratories (England). Cortisol concentration was determined using an Immulite 2000 analyser (Siemens Healthcare Diagnostics Inc., Belmont, CA) with a solid-phase competitive chemiluminescent enzyme immunoassay. CK and LDH were measured using a clinical chemistry analyser (Model AU640; Beckman Coulter, UK).

Instrumental meat quality

At slaughter, carcass data (weight, fat classification and conformation) were recorded according to the EU classification system. Carcass sides were split between the 9th and 10th rib and subcutaneous fat depth (mm) was measured at three points (0.25, 0.50, 0.75) around the *longissimus dorsi* muscle on both sides of the carcass. The mean of these values was taken as the subcutaneous fat depth for each animal (Kirkland *et al.*, 2007).

At four days post-slaughter two samples were taken from the *longissimus dorsi* muscle and aged at 3 °C, one until D7 and the other until D14 post-slaughter. At D7 pH_{ult} and colour (L*(lightness), a*(redness) and b*(yellowness)) were assessed using a Jenway 370 pH meter and a Chroma Meter CR-400, respectively. Both instruments were calibrated prior to measurements being taken. D7 and D14 samples were scored for marbling using the MSA scoring system, with the mean of D7 and D14 considered as the marbling score. Vacuum-packed samples were cooked for 50 minutes in a 70 °C water bath. Samples were weighed pre- and post-cooking, to allow cooking loss to be calculated:

$$\text{Cooking loss \%} = \left(\frac{\textit{pre cooking weight-post cooking weight}}{\textit{pre cooking weight}} \right) 100$$

Warner Bratzler Shear Force (WBSF) measurements were recorded using an Instron 3366 Universal Testing Instrument. Samples were cored parallel to the muscle fibres and 10 cores (sub-samples) of a 12.5 mm diameter were taken from each meat sample. All sub-samples were sheared perpendicular to the muscle fibres and the mean of the sub-samples was considered as the WBSF value for each meat sample.

Statistical analysis

All statistical analysis were completed using Genstat (16th edition). Analysis on rumen temperature and haematological variables were carried out using a linear mixed model with repeated measures. Animal was fitted as the subject factor and time point as a fixed effect. The correlation between time points was accounted for using an antedependence model of order 1. A one way ANOVA and Fishers Protected LSD with pH_{ult} group as treatment factor was used to analyse the data in Table 6. A simple linear regression analysis was used to determine correlation coefficients to assess the relationship between rumen temperature and haematological variables and instrumental meat quality. The models predicting meat quality characteristics (pH_{ult}, L*,a*,b*, cooking loss and WBSF) were developed using a stepwise multiple regression analysis, both forward and backward selection methodologies were employed. Explanatory variables included haematological variables (cortisol, CK and LDH) at slaughter (T3), and rumen temperature; combinations of these variables were compared to identify the best model. This model was then fitted to a multiple linear regression, and evaluated on the basis of residual variance.

Results and discussion

Mean rumen temperature (Table 1) rose significantly during both transport and lairage in comparison to that recorded during the basal period, furthermore, rumen temperature peaked during lairage, reaching 40.46 °C. The distance travelled in this study was short (42km), with the journey lasting only 46 minutes, followed by a 38 minute stationary waiting time prior to unloading. Thus, it is possible that rumen temperature did not have sufficient time to recover prior to the introduction of a second stressor (lairage) (Chacon *et al.*, 2005). In addition, bulls were all held in one group during lairage, and thus mixing occurred. It is likely that this caused social stress, as a result of aggressive behaviour to re-establish a social hierarchy (Cafazzo *et al.*, 2012), leading to a cumulative stressor effect of transportation and lairage. Lairage duration had no effect on mean or maximum rumen temperature.

Table 1. Mean and maximum rumen temperature during the basal period, transport and lairage

	Basal	Transport	Lairage	SED	Sig.
Mean	39.25 [a]	39.72 [b]	39.79 [b]	0.0903	<0.001
Maximum	39.93 [a]	39.98 [a]	40.46 [b]	0.0850	<0.001

Basal: 48 hour period prior to loading; Transport: loading to unloading; Lairage: unloading to slaughter

Haematological variables (Table 2) were also significantly elevated at slaughter in comparison to basal levels. The two-fold increase in cortisol indicates that a stress response was initiated during the pre-slaughter phase. However, the exact stage of the pre-slaughter phase (transport or lairage) which contributed to the observed rise, is unknown due to the sampling procedure. The rise in CK and LDH at slaughter likely occurred due to increased physical activity and possible muscle damage, associated with transportation and mixing during lairage (Losada-Espinosa *et al.*, 2018). This is further supported by the findings in Table 3, where CK concentration increases with increased pH_{ult}.

Table 2. Haematological variables of bulls during the basal period and at slaughter

	Basal	Slaughter	SED	Sig.
Cortisol (nmol/l)	33.9	68.5	5.74	<0.001
CK (ui/l)	284	900	139.7	<0.001
LDH (ui/l)	3,125	3,748	123.5	<0.001

Basal: mean of T1 & T2; CK: creatine kinase; LDH: lactate dehydrogenase

Carcass characteristics had no effect on pH_{ult} and therefore, these results are not shown in Table 3. Bulls with a $pH_{ult} > 6.2$ had a significantly greater mean rumen temperature during both transport and lairage. Furthermore, maximum rumen temperature during lairage was significantly different in each of the three pH_{ult} ranges. As expected, the instrumental meat quality measures differed according to pH_{ult}.

Prior to the pre-slaughter phase, bulls were managed similarly within a small, stable social group, and thus were naive to transportation and other stressors associated with the pre-slaughter phase. Therefore, it could be suggested that this naivety may have magnified the individual variability within the group (Stockman *et al.*, 2011), resulting in the wide range of pH_{ult} values observed in this study. A significantly greater maximum rumen temperature during the basal period for bulls with a $pH_{ult} > 6.2$ may indicate that these bulls were more easily raised or stressed within an environment in which they were habituated to. Therefore, these bulls could be considered to have an excitable temperament, which has previously been shown to lead to poorer meat quality (Hall *et al.*, 2011, Ponnampalam *et al.*, 2017).

When combined with haematological variables at slaughter, pre-slaughter rumen temperature has the ability to be used as an indicator of meat quality. Table 4 shows the models that were identified that best quantify the relationship between instrumental meat quality, and pre-slaughter welfare indicators. This provides valuable information for the red meat industry, which may allow preventative action to be taken prior to slaughter. Further research is required to further refine the pre-slaughter prediction of meat quality, taking into account animal factors and remedial treatments.

Table 3. Rumen temperature, haematological variables and instrumental meat quality according to ultimate pH

	Ultimate pH				
	<5.8	**5.8-6.2**	**>6.2**	**SED**	**F pr.**
Number of bulls (n)	19	11	10		
Basal RT (°C)	39.24	39.24	39.26	0.079	ns
Mean transport RT (°C)	39.65 [a]	39.64 [a]	39.94 [b]	0.103	<0.05
Mean lairage RT (°C)	39.55 [a]	39.63 [a]	40.43 [b]	0.262	<0.01
Maximum basal RT (°C)	39.83 [a]	39.80 [a]	40.25 [b]	0.143	<0.01
Maximum transport RT (°C)	39.87 [a]	39.90 [a]	40.28 [b]	0.132	<0.01
Maximum lairage RT (°C)	40.06 [a]	40.52 [b]	41.16 [c]	0.194	<0.001
Slaughter Cortisol (T3) (nmol/l)	62.1	76.5	72.1	14.15	ns
Slaughter CK (T3) (ui/l)	559 [a]	982 [b]	1,458 [c]	211.0	<0.001
Slaughter LDH (T3) (ui/l)	3,596	3,829	3,949	214.2	ns
L^* (Lightness)	39.56 [b]	36.53 [a]	35.86 [a]	1.160	<0.01
a^* (redness)	27.04 [c]	23.60 [b]	22.27 [a]	0.569	<0.001
b^* (blue/yellow)	10.56 [c]	8.22 [b]	6.98 [a]	0.497	<0.001
Marbling Score (MSA)	718	682	722	50.09	ns
Cooking loss D7 (%)	26.05 [c]	23.63 [b]	19.58 [a]	0.737	<0.001
Cooking loss D14 (%)	25.68 [b]	24.99 [b]	19.43 [a]	1.381	<0.001
WBSF D7 (kg)	4.70 [b]	5.18 [b]	3.43 [a]	0.341	<0.001
WBSF D14 (kg)	4.46 [b]	4.71 [b]	2.96 [a]	0.266	<0.001

RT: Rumen temperature

Table 4. Prediction of meat quality based on rumen temperature and post-slaughter haematological variables

Y	Model (X_1+X_2+X_3)	intercept	s.e.	t pr.	X_1	s.e.	t pr.	X_2	s.e.	t pr.	X_3	s.e.	t pr.	R^2
pH_{ult}	MaxLRT + T3Cort + T3CK	-7.69	3.39	0.029	0.330	0.084	<0.001	0.0016	0.0013	0.220	0.00017	0.0000872	1.950	53.1
L*	MaxLRT	120.5	30.2	<0.001	-2.045	0.747	0.009							14.3
a*	MaxLRT + T3CK	136.9	18.4	<0.001	-2.754	0.454	<0.001	-0.0086	0.0085	0.320				47.2
b*	MaxLRT + T3CK	67.40	17.6	<0.001	-1.422	0.441	0.003	-0.0009	0.0005	0.048				45.4
Cooking Loss D7	MaxLRT + T3CK	108.7	31.6	0.001	-2.072	0.793	0.013	-0.0013	0.0008	0.128				33.4
Cooking Loss D14	MaxLRT + T3Cort	112.1	41.2	0.010	-2.130	1.010	0.043	-0.0286	0.0190	0.141				9.2
WBSF D7	MeanLRT + T3CK	25.00	10.0	0.017	-0.507	0.255	0.054	-0.0004	0.0003	0.203				17.5
WBSF D14	MeanLRT + T3CK	26.12	8.08	0.003	-0.546	0.205	0.011	-0.0003	0.0002	0.300				23.2

MaxLRT = maximum lairage rumen temperature; MeanLRT = mean lairage temperature; T3CK = creative kinase at slaughter; T3Cork = cortisol at slaughter

Conclusion

In conclusion, rumen temperature and haematological variables were significantly elevated as a result of the stressors associated with the pre-slaughter phase. Therefore, rumen temperature can be used as a reliable measure of stress-induced hyperthermia. Furthermore, the observed relationship between rumen temperature and meat quality indicate that with further research rumen temperature has the potential to be used as predictor of meat quality prior to slaughter.

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References

Burdick, N.C., Carroll, J.A., Hulbert, L.E., Dailey, J.W., Willard, S.T., Vann, R.C., Welsh Jr., T.H. & Randel, R.D. (2010). Relationships between temperament and transportation with rectal temperature and serum concentrations of cortisol and epinephrine in bulls. *Livestock Science,* 129**:** 166–172.

Cafazzo, S., Magnani, D., Cala, P., Razzuoli, E., Gerardi, G., Bernardini, D., Amadori, M. & Costa, L.N. (2012). Effect of short road journeys on behaviour and some blood variables related to welfare in young bulls. *Applied Animal Behaviour Science,* 139**:** 26–34.

Chacon, G., Garcia-Belenguer, S., Villarroel, M. & Maria, G.A. (2005). Effect of transport stress on physiological responses of male bovines. *Deutsche Tierarztliche Wochenschrift,* 112**:** 465–469.

Chulayo, A.Y. & Muchenje, V. (2017). Activities of some stress enzymes as indicators of slaughter cattle welfare and their relationship with physico-chemical characteristics of beef. *Animal,* 11**:** 1645–1652.

Ferguson, D.M. & Warner, R.D. (2008). Have we underestimated the impact of pre-slaughter stress on meat quality in ruminants? *Meat Science,* 80**:** 12–19.

Hall, N.L., Buchanan, D.S., Anderson, V.L., Ilse, B.R., Carlin, K.R. & Berg, E.P. (2011). Working chute behavior of feedlot cattle can be an indication of cattle temperament and beef carcass composition and quality. *Meat Science,* 89**:** 52–57.

Kirkland, R.M., Patterson, D.C., Keady, T.W.J., Moss, B.W. & Steen, R.W.J. (2007). Beef production potential of Norwegian Red and Holstein-Friesian bulls slaughtered at two ages. *Animal,* 1**:** 1506–1514.

Lister, D. Muscle metabolism and animal physiology in the dark cutting condition. In: Dark-cutting in cattle and sheep. Proceedings of an Australian workshop. Australian Meat & Live-stock Research and Development Corporation, 1988 Sydney South, NSW, Australia.

Losada-Espinosa, N., Villarroel, M., Maria, G.A. & Miranda-De La Lama, G.C. (2018). Pre-slaughter cattle welfare indicators for use in commercial abattoirs with voluntary monitoring systems: A systematic review. *Meat Science,* 138**:** 34–48.

Ponnampalam, E.N., Butler, K.L., Burnett, V.F., Mcdonagh, M.B., Joe, L., Jacobs, J.L. & Hopkins, D.L. (2013). Aged vacuum packaged lamb cuts are less brown than fresh muscle cuts under simulated retail display. *Food Nurtition Science,* 4**:** 147–153.

Ponnampalam, E.N., Hopkins, D.L., Bruce, H., Li, D., Baldi, G. & El-Din Bekhit, A. (2017). Causes and Contributing Factors to "Dark Cutting" Meat: Current Trends and Future Directions: A Review. *Comprehensive Reviews in Food Science and Food Safety,* 16**,** 400–430.

Proctor, H.S. & Carder, G. (2015). Nasal temperatures in dairy cows are influcenced by positive emotional state. *Physiology and Behaviour,* 138**:** 340–344.

Stockman, C.A., Collins, T., Barnes, A.L., Miller, D., Wickham, S.L., Beatty, D.T., Blache, D., Wemelsfelder, F. & Fleming, P.A. (2011). Qualitative behavioural assessment and quantitative physiological measurement of cattle naive and habituated to road transport. *Animal Production Science,* 51**:** 240–249.

Tarrant, P.V. & Lacourt, A. (1984). Effect of glucocorticoid, insulin and glucose treatment on glycogen content in young bulls. *British Veterinary Journal,* 140**:** 337–345.

Teke, B., Akdag, F., Ekiz, B. & Ugurlu, M. (2014). Effects of different lairage times after long distance transportation on carcass and meat quality characteristics of Hungarian Simmental bulls. *Meat Science,* 96**:** 224–229.

Warriss, P.D. & Brown, S.N. (2008). *Identifying practical ways to reduce the prevalence of dark cutting beef (DCB) in young bulls by better animal handling anti-mortem* [Online]. Available: http://www.eblex.org.uk/wp/wp-content/uploads/2013/04/darkcuttingbeef/_181010-final-report.pdf. [Accessed].

Session 5

Precision Livestock Farming Technology for Grass Management

Improved estimation of grassland biomass using machine learning and satellite data

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Abstract

Monitoring management practices in grasslands such as grazing and silage cutting at field scale helps to understand the yield and its carrying capacity. Traditional methods for grassland monitoring can be time consuming and labour-intensive. In this study we estimate grassland biomass at a farm-level using remote-sensing. For a full understanding it is important to monitor the grass growth and utilisation on the farm with a high temporal and spatial resolution satellite images which can be used for monitoring biomass, phenology and growth rate of a pasture.

The main goal is to determine grass growth rate using satellite and weather data (Moorpark, Co. Cork in Ireland is used as an example). Normalised difference vegetation index (NDVI) from Landsat-8 satellite, along with weather data such as temperature, rainfall and potential evapotranspiration data were used to model grass yield and compared with ground measurements and traditional biophysical grass growth model outputs. Adaptive neuro-fuzzy inference system (ANFIS) was used to generate models to predict and map grass biomass. The models were evaluated using Mean Squared Error, Root Mean Squared Error (RMSE) and Symmetric Mean Absolute Percent Error (SMAPE). The final model was used to predict the biomass for the subsequent year for validation purpose. The resulting grass growth rate will help a farmer in understanding the maximum potential from their farm as well as the stocking rate on the farm.

Keywords: ANFIS, Landsat-8, grassland, machine-learning biomass

Introduction

Ireland has an area of 69,798 km², agriculture occupies ~62% of the area of the Republic of Ireland (ROI), with grass as the foundation of Irish Agriculture occupying > 80% of that and 62% of the land is used for agriculture (O'Mara, 2008). The grasslands are used for forage and food production. Improved grazing management on farms leads to greater forage production, and enhanced profitability (Dillon *et al.*, 2005). Monitoring grasslands at regular intervals leads to improved farm management (Ali, 2016). Monitoring of grassland can be undertaken by ground level measurement and using satellite data at different scales. Ground level data is collected using a rising plate meter or by manually cutting and drying the grass on the farm (Ali, 2015). Satellite data at different spatial resolutions can also be used. In this study Landsat-8 30 m resolution data was used to estimate grass growth rate using machine learning approach.

Materials and methods

Study area

The study was Moorepark Research Farm (Lat: 50°7N, Long: 8°16W) in Co. Cork in the south of the Republic of Ireland. The site contains 136 paddocks for various experiments. The map of the farm with paddock names is given in Figure 1. The site covers an area of approximately 100 hectares. Figure 1 shows the test farm location with the extent of the study area.

Figure 1. Study area: Moorepark farm

PastureBase Ireland data and pre-processing

The ground level data used for validation of the model was extracted from PatureBase Ireland which is a web based grassland management decision support tool collecting and storing grassland data from farmers (Hanrahan *et al.*, 2017). It contains information on grass cover, grazing dates and residual grazing height, etc. at a paddock level. The grass cover data for each paddock and each measurement date was downloaded from PastureBase Ireland into Microsoft Excel to form a database for 2017 and 2018. The data for Moorepark farm in PBI is available from 2016 onwards. The database contains weekly geocoded grass cover yield (kg dry matter (DM)/ha), grazing dates and silage cutting dates.

Satellite data processing

Landsat-8 surface reflectance Level-2 data for the location for 2017 and 2018 was downloaded from the USGS Earth Explorer data portal (https://earthexplorer.usgs.gov/). The images were inspected visually for clouds and shadow as clouds and shadows hinder the satellite to collect the true reflectance from the ground. Normalised difference vegetation index (NDVI) was computed using bands 4 (red: 0.64 – 0.67 nm) and 5 (near infrared: 0.85 – 0.88 nm). The data were cropped according to the farm boundary. Spatial averaging of the pixels of the images for the whole farm was performed. Hence, the satellite data is at farm-level.

Meteorological data

The meteorological data such as minimum temperature (°C), maximum temperature (°C), mean temperature (°C), potential evapotranspiration (mm), soil moisture deficit (mm) and global radiation (J/cm sq.) was downloaded from Met Éireann - the Irish Meteorological Service (https://www.met.ie/climate/available-data/historical-data) for 2017 and 2018. The data was downloaded for Moorepark Research Farm (station no. 575).

Methodology

Landsat-8 daily surface reflectance was converted into vegetation index: NDVI for 2017 and 2018. There were 91 images for 2017 and 2018 out of which 18 images were selected as they were cloud-free images. Linear interpolation was applied to fill the gaps resulting from missing data due to clouds and shadows. The dataset was standardised to a zero mean and unit variance. Mean NDVI was calculated for the farm using zonal statistics. Time-series of NDVI was generated for the farm. A time-series for grass cover from PatureBase Ireland was also generated for 2017 and 2018. A machine learning model called Adaptive Neuro-Fuzzy Inference Systems (ANFIS) was developed in R to estimate the grass growth rate (kg DM/ha/day). The 2017 data were used for training the model, whereas data for 2018 were used as testing data. The work-flow of this study is shown in Figure 2.

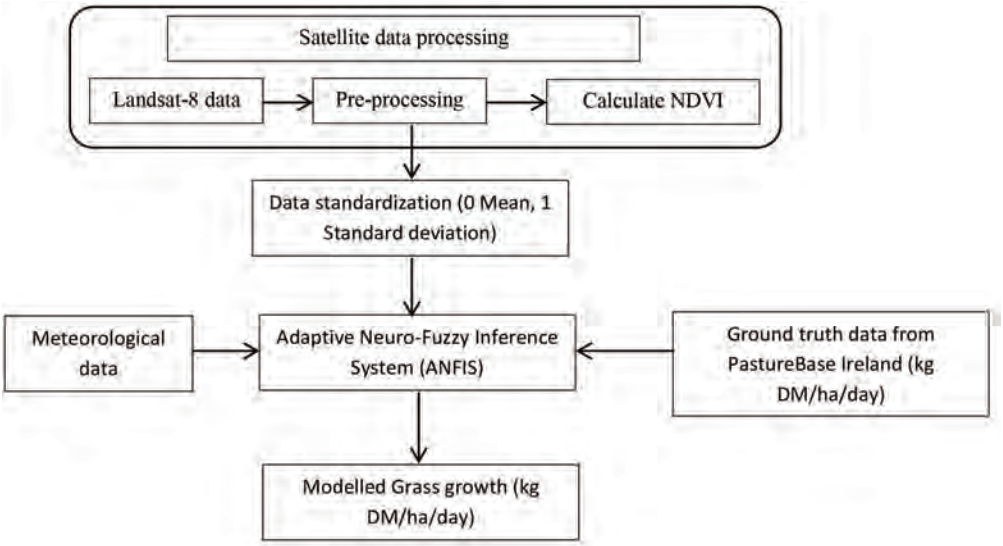

Figure 2. Methodology

Model development

Adaptive Neuro Fuzzy Inference Systems (ANFIS) model

Adaptive Neuro Fuzzy Inference Systems is a multi-layered neural network with the combination of artificial neural network (ANN) and fuzzy logic (Ali I. *et al.*, 2016) as shown in Figure 3. The architecture of ANFIS was first introduced by Jang in 1993. It is a five layered structure as described below:

Layer 1 Fuzzy layer: Defines the membership function. The parameters in this layer are called premise parameters.

Layer 2 Product layer: Multiplies the incoming signals from the layer 1.

Layer 3 Normalised layer: Calculates the ratio of each weight to the sum of all the weights. The output of this layer is called normalised firing strength.

Layer 4 Adaptive layer: All the nodes in this layer are adaptive nodes. The parameters in this layer are called consequent parameters.

Layer 5 Output layer: Contains a single node which is a fixed node. It computes the summation of all the incoming signals.

The input data for the model was divided into training and testing datasets. The 2017 data were used for training the model and the 2018 data were used to test the model developed.

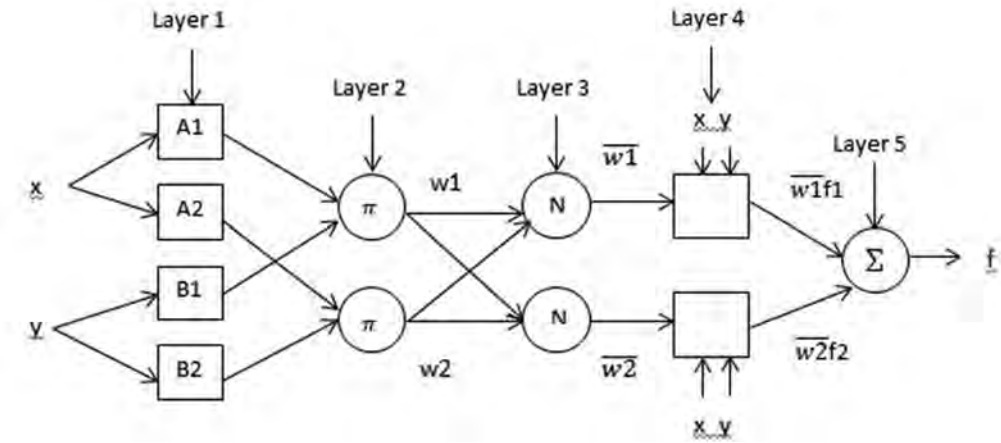

Figure 3. ANFIS architecture

Results and discussion

Machine learning algorithms were compared to estimate grassland biomass (Ali *et al.*, 2016), and as a result ANFIS used for modelling outperformed the conventional mathematical and statistical (MLR) modelling approaches. Three performance indicators were used for this work, i.e. Mean Absolute Error (MSE), Root Mean Squared Error (RMSE) and Symmetric Mean Absolute Percent Error (SMAPE). The model successfully identified the seasonal phenological curve which matches the curve with the training data with growth peak during the growing season and a secondary peak in the autumn as shown in the actual and predicted time series of grass growth (kg DM/ha/day) for the Moorepark site (Figure 1). The data was normalised before inputting it to the model. The training data were used to fit the ANFIS model. Further, training data were also used to predict the grass growth rate. The predicted grass growth data using the fitting data along with the actual grass growth data is shown in Figure 4. The figure shows that the predicted data is following the actual data from the training data, except it under-predicts at some points.

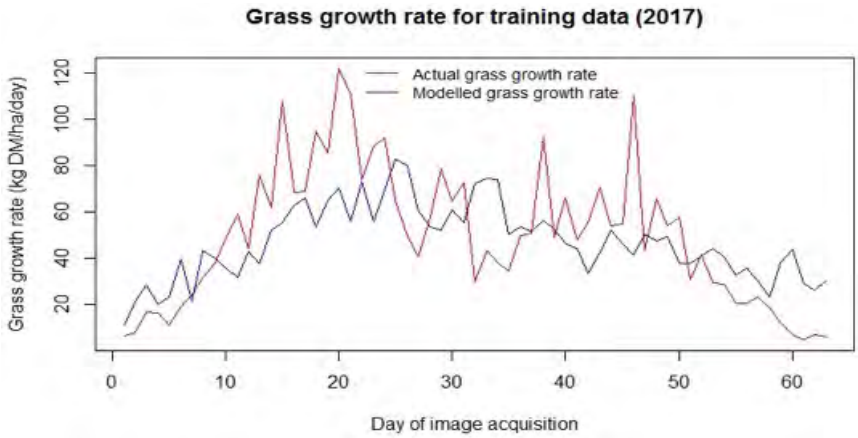

Figure 4. Grass growth: actual and predicted for training data

The data from 2018 for Moorpark farm was used to test the model. The actual grass growth and predicted grass growth data are shown in Figure 5. It can be seen from the Figure 5 that the model is performing well in the first half of the curve (following the phonological curve), which is the first half of the year. During the second half of the year (after June), the model over-predicts the grass growth rate. The reason for over-estimating is that the year 2018 had extreme weather with a drought in Ireland. The model could not take into account the effect of drought in the second half of the year.

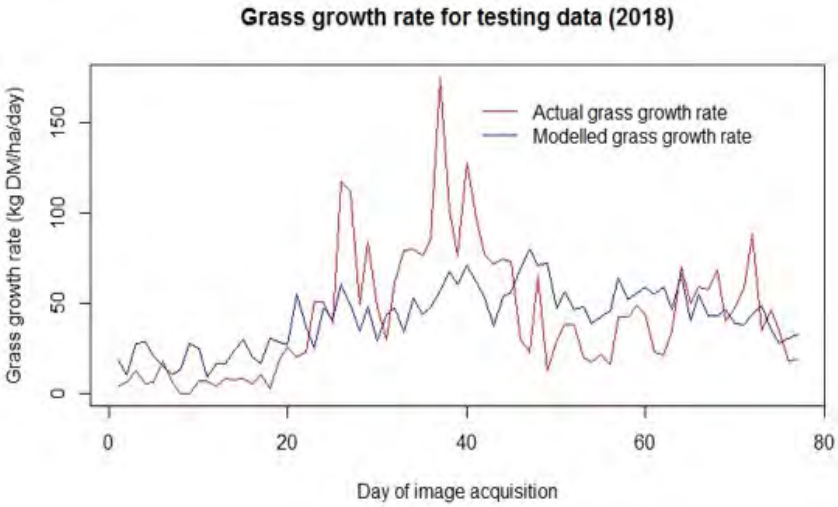

Figure 5. Grass growth: actual and predicted for testing data

Figure 6 shows the scatter plots of actual and predicted grass growth. Our study showed the grass growth values modelled by ANFIS (MSE = 0.050, RMSE = 0.225, SMAPE= 16.96).

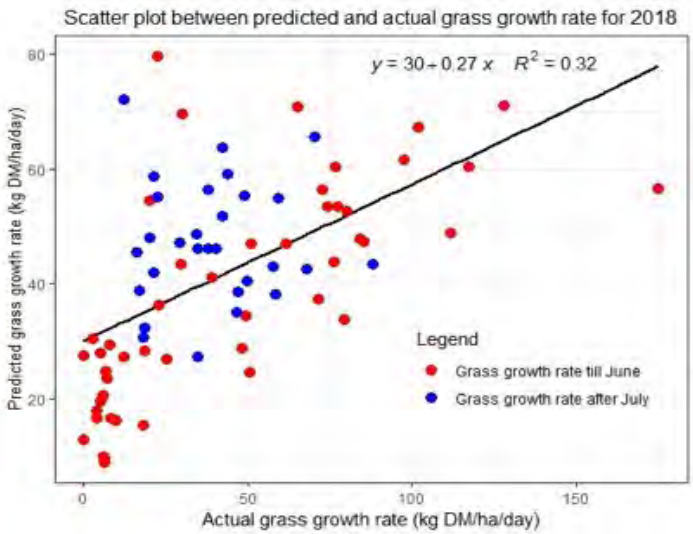

Figure 6. Scatter plot between predicted/simulated and actual grass growth rate for 2018

Conclusions

The ANFIS model with Landsat-8 data with all other meteorological variables was tested using mean square error (MSE), coefficient of determination (R^2) and Symmetric Mean Absolute Percent Error (SMAPE). The results show low MSE and RMSE for the testing data. The prediction using this model was well aligned with the ground level data from PastureBase Ireland data. The model over-predicted yield during the second half of 2018. This is because 2018 was a drought-affected year which the model is unable to predict. Because of this it is important to increase the training data for the model geographically as machine learning model needs much wider and deeper training data. Future work aims to refine the model for other sites in Ireland and to include the effects of extreme weather conditions. Sentinel-2 data will also be incorporated into the model in the future.

References

Ali, I., Greifeneder, F., Stamenkovic, J., Neumann, M. and Notarnicola, C. (2015). Review of Machine Learning Approaches for Biomass and Soil Moisture Retrievals from Remote Sensing Data. *Remote Sensing,* 7: 16398–16421.

Ali, I., Cawkwell, F., Dwyer, E., and Green, S. (2016). Modeling Managed Grassland Biomass Estimation by Using Multitemporal Remote Sensing Data—A Machine Learning Approach. *IEEE Journal of selected topics in applied earth observations and remote sensing,* 10: 3254–3264.

Ali, I., Cawkwell, F., Dwyer, E., and Green, S. (2016). Satellite remote sensing of grasslands: from observation to management. *Journal of Plant Ecology,* 9: 649–671.

Dillon, P., Roche, J.R., Shalloo, L. and Horan, B. (2005). Optimising financial return from grazing in temperate pastures. *Utilisation of grazed grass in temperate animal systems Proceedings of a satellite workshop of the XXth International Grassland Congress, Cork, Ireland* 131–147.

Hanrahan, L., Geoghegan, A., O'Donovan, M., Griffith, V., Ruelle, E., Wallace, M. and Shalloo, L. (2017). PastureBase Ireland: A grassland decision support system and national database. *Computers and Electronics in Agriculture,* 136: 193–201.

O'Mara F (2008). Country Pasture/Forage Resource Profile/Ireland, FAO (2008).

Kikuyo grass (Cenchrus clandestinus Hochst. ex Chiov) growth simulation using the BASGRA model

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Abstract

Mathematical models designed to estimate grass growth are useful tools for short-term decision making, and to design strategies for farm adaptation to global climate change. For grass growth modeling it is necessary to consider grass growth variability due to soil quality differences, grass management, and interactions between grass and animals. The aim of this work was to estimate three parameter sets for the BASGRA model, in order to estimate Kikuyo grass dry matter (DM) yield (DMY) in a grass-based dairy farm. Between April and October 2017, 74 grass samples were randomly taken at the Universidad de Antioquia dairy farm in North-Antioquia, Colombia. Dry matter yield in each sample was classified into one of three DMY categories (High, Medium and Low). Then, the database from each DMY category was used to perform Bayesian calibration of BASGRA model. The Concordance Correlation Coefficient (CCC) was used to assess the consistency between grass yield predicted and observed. The DMY categories distribution was 12, 60 and 28% of total grass samples for High, Medium and Low, respectively. The mean grass growth rate was 9.7, 5.6 and 3.1 g of DMY / m^2 / day for High, Medium and Low, respectively. A high concordance was found (CCC = 0.91) between the DMY predicted by the calibrated BASGRA model and the DMY observed in the grass samples. The results of this work showed that a model's calibration process which takes into account the grass growth heterogeneity allows precise grass growth estimations.

Keywords: BASGRA, Markov Chain - Monte Carlo, Bayesian Calibration.

Introduction

Dairy farms in North-Antioquia, Colombia are grass-based systems where dairy cows feed is supplemented with grains. Kikuyo grass (*Cenchrus Clandestinus* Hochst. Ex Chiov) is widely used as feed base on these farms due to its aggressive growth in relation to other vegetal species. Kikuyo grass is resistant to trampling and responds positively to fertilization. However, its nutritional characteristics (e.g. high crude protein and low non-fibrous carbohydrate contents) limits milk production (Correa, 2011).

Estimation of the daily grass offered (i.e. the amount of grass per area unit) is a routine practice in Colombian dairy farms. Traditionally, grass offered is estimated using the grass yield in some quadrants (1 m^2) manually cut. This technique, in addition to being destructive, consumes a lot of time and requires numerous samples to obtain reliable estimations (Catchpole & Wheeler, 1992). Other methods are based on indirect indices which represent the relationship, as far as possible linear, between grass biomass and some easy-to-measure variables. López & González (2003) compared several non-destructive methods (i.e. visual estimates, manual and electronic grass meters, and remote sensing). López & González (2003) did not identify a most appropriate method and concluded that factors such as climate variations, soil characteristics, plant phenology, grass management, and species composition should be taken into account to perform local calibrations of non-destructive methods.

The traditional methods and techniques outlined above, whether destructive or not, have allowed estimation of grass produced, in the past. But strategic planning, which guarantees the farms' sustainability in the long term, needs tools which help to predict future grass yield due to global climate change. To simulate grass growth and quality, in a climate change context, several models have been developed: BASGRA (Höglind *et al.,* 2016), CATIMO (Bonesmo y Bélanger, 2002), IFSM (Rotz *et al.,* 2015), MCPy (Stilmant *et al.,* 2001), PaSim (Graux *et al.,* 2011), QUAL (Gustavsson *et al.,* 1995), SPACSYS (Wu *et al.*, 2007) and STICS (Jégo *et al.,* 2013), among others. These models represent physiological and morphological changes in plants, and their interaction with the environment (Van Oijen & Höglind, 2016).

Given soil fertility differences inside a prairie and grass management, localized calibrations of a grass growth model are required. In grass-based dairy farms, understanding and modeling grass growth is complex, due to the interactions between animals and grass. During grazing, the animals transfer significant amounts of nutrients randomly and systematically to the prairie, which generates or exacerbates soil variability (Snow *et al.,* 2014) and grass yield. This complexity constitutes a challenge for grass growth model development and calibration. The aim of this work was to calibrate the BASGRA model to predict Kikuyo grass yield taking into account the prairie heterogeneity on a dairy farm.

Materials and methods

Location

The data for model calibration were obtained at the Universidad de Antioquia dairy farm. This is a grass-based dairy farm located in a low mountain rain forest habitat in North-Antioquia, Colombia, with a height above sea level between 2,471–2,499 m, an average temperature of 16 °C and coordinates N 6°27'094, W 75°32'678.

Model description

BASGRA is a process-based model that simulates annual pasture processes: growth and development, and winter survival. Interactions with the atmospheric and soil environment are simulated in some detail. The role of pasture management (i.e. grazing, cutting and irrigation) is included. During winter, the model tracks the dynamics of water in its various forms: ice formation under and on the ground, snow cover, liquid water storage in the snow, and soil and surface pools. Damage by frost and anaerobic conditions under the ice, which accelerate senescence according to the level of maturity of the plant, is also represented. BASGRA has 23 state variables, 13 of these variables quantify the state of the plants, and the others represent the environment above and below the soil in which plants grow. Three types of state variables can be distinguished: variables for mass, shape, and function. To execute the model, BASGRA requires a time series of the following climatic variables: radiation, temperature, precipitation, wind velocity and relative humidity. The latter two are only used in calculating the potential rates of evaporation and perspiration. In addition, the model requires time series that indicate on which days the grass is cut. The atmospheric concentration of CO_2 is constant. Soil properties, such as water retention parameters, are also provided as constants. BASGRA does not simulate some variables that are very important in pasture productivity, such as digestibility and fiber content of the harvested material, but these variable are closely related to the leaf/stem ratio, which the model can calculate (Van Oijen *et al.,* 2015).

Calibration

The model calibration process was carried out using the R codes developed by Van Oijen & Höglind (2016) in Rstudio software The calibration proposed by Van Oijen & Höglind (2016) consists of three steps: 1) definition of 'a priori' distributions for each parameter, 2) definition of likelihood function, and 3) sampling of 'a posteriori' distributions of each parameter. In the first step, the beta distribution and the mean, minimum and maximum parameters values proposed by Van Oijen *et al.* (2015) were used. In the likelihood function, used to quantify the mismatch between model outputs induced by each parameter vector and observed data, the grass dry matter yield (DMY) observed and predicted were used. The distance between the predicted and observed DMY was calculated with the Normalized Root Mean Square Error (NRMSE) as proposed by Van Oijen *et al.* (2015). In step three, samples from 'a posteriori' distribution were generated using the Markov Chains - Monte Carlo (MCMC) method and the Metropolis algorithm (Metropolis *et al.,* 1953). To ensure convergence on all chains, the length of the chains was 200,000.

The grass growth heterogeneity observed at the Universidad de Antioquia dairy farm was included in model calibration. The DMY observed in each grass sample from the farm were classified into three categories: High (> 8 DMY / day), Medium (between 4 - 8 DMY / day) and Low (< 4 DMY / day). These categories ware used to perform three independent calibrations of the BASGRA model. In each calibration process, the Kikuyo DMY and the climatic conditions observed during grass growth were used. DMY and weather data were obtained as follows:

Kikuyo DMY

At 10, 20, 30, and 40 days after grazing, 74 Kikuyo grass samples were randomly cut at the Universidad de Antioquia dairy farm. The grass cut area per sample was 1 m^2. The grass was cut to a height between 10–15 cm above the ground. For DMY (g of DMY / m^2) determination, a grass sub-samples (200 g) were dried at 70 °C by 72 hours.

Weather station

Climatic variables were measured using a Vantage Pro2™ (Davis Instruments) meteorological station. The data were collected over 111 days between April and October 2017. In model calibration was taken into account the daily: average, minimum and maximum temperatures (°C), mean relative humidity (%), rainfall (mm), mean wind speed (meters per second), and solar radiation (Mega Joules per square meter).

Data analysis

The SAS University Edition (SAS Institute, 2018) software was used in statistical analysis. To establish a significant difference among the three grass categories (i.e. High, Medium and Low), a completely randomized design model and the Tukey Test were used. To establish the concordance between the DMY predicted after calibration and the DMY observed, Lin's Concordance Correlation Coefficient was used (CCC, Lin 1989).

Results and discussion

Weather and DMY

Table 1 shows the climatic conditions during the sampling period. Rainy days corresponded to 26% of total sampling time. A positive correlation was observed between DMY and rainfall (0.45), and between DMY and solar radiation (0.50). The maximum temperature was negatively correlated with DMY (-0.46).

Table 1. Weather during the sampling period

Variable	Days	Median	Standard deviation	Minimum	Maximum
T	111	14.8	1.1	12.0	17.1
TMMXI	111	19.5	1.1	15.7	21.7
TMMNI	111	9.9	2.0	3.4	14.9
RH	111	85.1	3.8	71.6	92.5
RAINI	111	5.7	10.4	0	75.7
WNI	111	1.3	0.5	0.3	3.4
GR	111	16.4	4.7	3.1	24.1

T = mean temperature (°C), TMMXI = maximum temperature (°C), TMMNI = minimum temperature (°C), RH = mean relative humidity (%), RAINI = Rain (mm/day), WNI = mean wind speed (m/sec), GR = Solar radiation (MJ/m^2/day)

Table 2 shows the DMY categories distribution and the grass growth rates in each DMY category. The Medium DMY category had a high prevalence in the prairie (60%). A significant difference was found for growth rate among the DMY categories.

Table 2. Grass dry matter yield in the three categories

Grass categories	N	%	Grass growth rate (g of DMY/m^2/day)	Standard deviation	Minimum	Maximum
High	9	12	9.9[a]	1.54	8.2	12.4
Medium	44	60	5.6[b]	0.99	4.0	7.9
Low	21	28	3.1[c]	0.57	2.2	3.9

[a, b, c] = indicate significant difference ($p < 0.05$)

Bayesian calibration

Table 3 presents, for each BASGRA model parameter, the estimated value by Bayesian calibration in each DMY category (High, Medium and Low). The parameter description was presented by Van Oijen *et al.*, 2015.

Table 3. BASGRA model parameters for three Kikuyo grass dry matter yield categories

Parameter	Categories			Parameter	Categories		
	High	Medium	Low		High	Medium	Low
LOG10CLVI	1.2	1.4	1.4	TRANCO	8.2	7.8	8.2
LOG10CRESI	1.02	0.77	0.67	YG	0.85	0.83	0.83
LOG10CRTI	0.7	1.1	1.0	WCI	0.30	0.30	0.30
CSTI	0	0	0	WCAD	0.011	0.011	0.011
LOG10LAII	0	0	0	WCWP	0.09	0.06	0.06
PHENI	0.01	0.01	0.01	WCFC	0.66	0.67	0.66
TILTOTI	1,969	1,696	1,558	WCWET	1.0	1.0	1.0
FRTILGI	0	0	0	WCST	0.44	0.44	0.44
LT50I	-4.8	-4.8	-4.8	WpoolMax	50.0	50.0	50.0
CLAIV	0.46	0.43	0.51	Dparam	0.0033	0.0032	0.0031
COCRESMX	0.15	0.15	0.13	FGAS	0.41	0.39	0.40
CSTAVM	1.0	1.0	1.0	FO2MX	0.20	0.20	0.20
DAYLB	0.35	0.39	0.37	gamma	59.5	58.5	67.3
DAYLP	0.70	0.63	0.64	Hparam	0.01	0.01	0.01
DLMXGE	0.98	0.92	1.00	KRDRANAER	0.22	0.26	0.24
FSLAMIN	0.29	0.44	0.55	KRESPHARD	0.02	0.01	0.01
FSMAX	0.69	0.69	0.69	KRSR3H	0.93	1.00	0.99
HAGERE	0.86	0.79	0.80	KRTOTAER	1.9	2.1	2.1
K	0.47	0.48	0.48	KSNOW	0.03	0.03	0.04
LAICR	4.1	3.6	3.8	LAMBDAsoil	171,600	167,400	178,200
RDRSMX	0.06	0.06	0.06	SWret	0.10	0.10	0.10
RDRTEM	0.00094	0.00097	0.00104	SWrf	0.01	0.01	0.01
RGENMX	0.01	0.01	0.01	THARDMX	14.7	14.7	14.5
ROOTDM	0.84	0.66	0.75	TmeltFreeze	0	0	0
RRDMAX	0.01	0.01	0.01	TrainSnow	0.01	0.01	0.01
RUBISC	6.2	5.1	5.4	TsurfDiff	0.36	0.54	0.56
SHAPE	0.60	0.58	0.50	KLUETILG	0.41	0.62	0.52
SIMAX1T	0.0036	0.0048	0.0045	FRTILGG1I	0.20	0.12	0.08
SLAMAX	0.06	0.06	0.06	DAYLG1G2	0.64	0.58	0.61
TBASE	3.4	3.5	3.6	RGRTG1G2	0.88	0.88	0.91
TCRES	1.6	2.0	2.0	RDRTMIN	0.008	0.010	0.011
TOPTGE	11.0	12.4	12.9	TVERN	20.0	20.0	20.0

Figure 1 shows the linear relationship between the DMY predicted by the calibrated BASGRA model and the DMY observed (CCC = 0.91) at Universidad de Antioquia dairy farm.

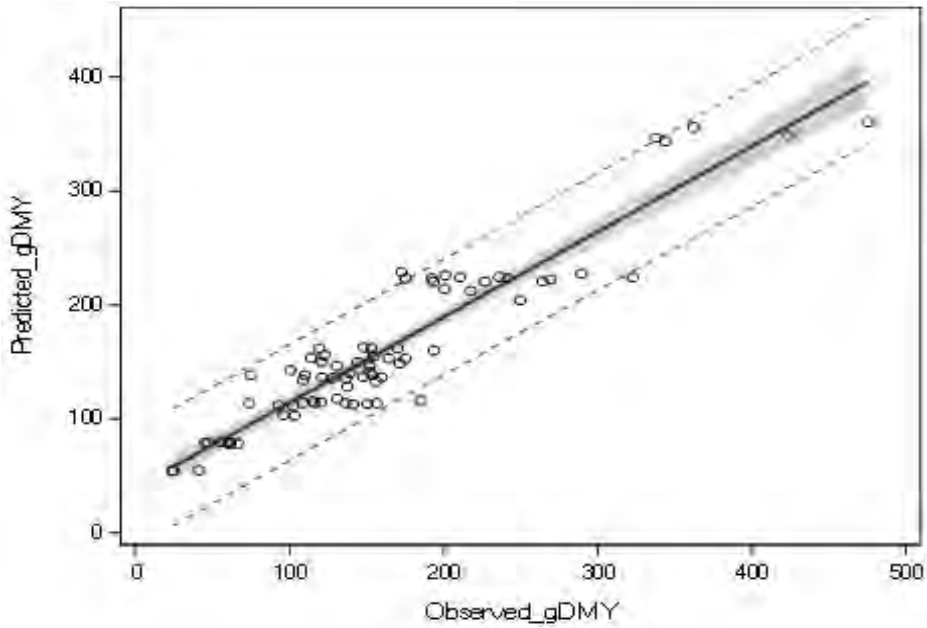

Figure 1. Concordance between predicted and observed grass dry matter yield (g/day)

The models' predictive capacity was hampered by incomplete processes representations, structural model errors or lack of data for parameterization (Van Oijen *et al.,* 2018). Some authors (Van Oijen *et al.,* 2011, 2013) have identified the need to develop and compare models in a probabilistic framework, which allows a rigorous quantification of uncertainty. In this sense, Van Oijen *et al.* (2015) propose that the calibration Bayesian is a successful method for parameters search in process-based models.

In the present work, the Bayesian calibration results suggest that BASGRA model predicts Kikuyo DMY accurately (CCC = 0.91, Figure 1) when the heterogeneity of prairie growth is considered in calibration. However, Van Oijen & Höglind (2016) found that BASGRA model complies with general applicability requirements, without the need for site-specific parameterization, at least for the geographical area and production systems analysed by these authors. Probably, the calibrated model performance in this work was due to the use of just one variable (i.e. DMY / m^2) in the calibration likelihood function. This undemanding calibration has been successfully used by some authors (Van Oijen & Höglind, 2016). These authors explain that it is a more forgiving calibration that increases the goodness of fit, although perhaps the model does not adequately represent some underlying processes. Additionally, the grass aerial biomass turns out to be the most relevant variable in a productive point of view, and its determination is a routine practice in farms.

Conclusions

The calibrated BASGRA model performance in this work suggest that process-based models are useful to estimate Kikuyo grass yield in Colombian dairy farms. However, in order to obtain a better model performance in Kikuyo grass yield estimation, it is important to make localized calibrations considering grass management.

Acknowledgements

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References

Bonesmo, H. and Bélanger, G. (2002). Timothy yield and nutritive value by the CATIMO Model: II. Digestibility and fiber. *Agronomy Journal,* 94: 345–350.

Catchpole, W.R., y Wheeler, C.J. (1992). Estimating plant biomass: a review of techniques. *Austral Ecology*, 17(2): 121–131.

Correa Cardona, H.J. (2011). Efecto del manejo del pastoreo y la suplementación alimenticia en vacas lactantes de sistemas especializados sobre su metabolismo energético y proteico y el contenido de proteína en la leche (Doctoral dissertation, Universidad Nacional de Colombia).

Graux, A.I., Gaurut, M., Agabriel, J., Baumont, R., Delagarde, R., Delaby, L. and Soussana, J.F. (2011). Development of the pasture simulation model for assessing livestock production under climate change. *Agriculture, Ecosystems and Environment,* 144: 69–91.

Gustavsson, A.M., Angus, J.F. and Torssell, B.W.R (1995). An integrated model for growth and nutritional value of timothy. *Agricultural Systems,* 47: 73–92.

Höglind, M., Van Oijen, M., Cameron, D. & Persson, T. (2016). Process-based simulation of growth and overwintering of grassland using the BASGRA model. *Ecological Modelling,* 335: 1–15.

Jégo G, Bélanger G, Tremblay GF, Jing Q and Baron VS (2013). Calibration and performance evaluation of the STICS crop model for simulating timothy growth and nutritive value. *Field Crops Research,* 151: 65–77.

López Díaz, J.E., y González-Rodríguez, A. (2003). Measuring grass yield by non-destructive methods. In Optimal forage systems for animal production and the environment. *Proceedings of the 12th symposium of the European Grassland Federation* 8: 569-572.

Lin, L. (1989). A concordance correlation coefficient to evaluate reproducibility. *Biometrics* 45, 255–268.

Metropolis N, Rosenbluth AW, Rosenbluth MN, Teller AH, Teller E (1953). Equation of state calculations by fast computing machines. *J Chem Phys,* 21: 1087–1092.

Rotz CA, Corson MS, Chianese DS, Hafner SD, Jarvis R and Coiner, C.U. (2015). The integrated farm system model – reference manual – version 4.2, September 2015.

Snow, V.O., Rotz, C.A., Moore, A.D., Martin-Clouaire, R., Johnson, I.R., Hutchings, N.J., y Eckard, R.J. (2014). The challenges–and some solutions–to process-based modelling of grazed agricultural systems. *Environmental Modelling Y Software*, 62: 420–436.

Stilmant, D., Rabier, F., Dufrasne, S., Oger, R. and Buffet, D. (2001). Prévision des quantités et des qualités des fourrages disponibles: aide à l'établissement d'une stratégie alimentaire à l'échelle de l'exploitation et de la région agricole. Rapport final. Telsat 4. Ministère des Classes moyennes et de l'Agriculture, CRA, Section Biométrie, Gestion des données et Agrométéorologie, Programme de recherche 'Observation de la terre par satellite'. Gembloux, 85pp. (in French).

Van Oijen, M., Cameron, D.R., Butterbach-Bahl, K., Farahbakhshazad, N., Jansson, P.E., Kiese, R., ... y Yeluripati, J.B. (2011). A Bayesian framework for model calibration, comparison and analysis: Application to four models for the biogeochemistry of a Norway spruce forest. *Agricultural and Forest Meteorology*, 151(12): 1609–1621.

Van Oijen, M., y Höglind, M. (2016). Toward a Bayesian procedure for using process-based models in plant breeding, with application to ideotype design. *Euphytica*, 207(3): 627–643.

Van Oijen M, Höglind M, Cameron DR, Thorsen SM (2015). BASGRA_2014. Available in https://zenodo.org/record/27867#.WowZtTZREdU.

Van Oijen, M., Bellocchi, G., y Höglind, M. (2018). Effects of climate change on grassland biodiversity and productivity: the need for a diversity of models. *Agronomy*, 8(2): 14.

Van Oijen, M., Reyer, C., Bohn, F.J., Cameron, D.R., Deckmyn, G., Flechsig, M., ... & Lasch, P. (2013). Bayesian calibration, comparison and averaging of six forest models, using data from Scots pine stands across Europe. *Forest Ecology and Management*, *289*: 255–268.

Wu L, McGechan MB, McRoberts N, Baddeley JA and Watson CA (2007). SPACSYS: integration of a 3D root architecture component to carbon, nitrogen and water cycling-model description. *Ecological Modelling,* 200: 343–359.

How accurate is the Grasshopper® system in measuring dry matter quantity of Swiss and Danish grassland?

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Abstract

The interest in pasture-based dairy systems in Europe increases, as it is a cost-effective way to provide feed. The precise estimation of feed on pastures is complex and laborious. The Grasshopper® system promises a solution. It is a semi-automated rising plate meter to estimate herbage quantity of grasslands. The system measures compressed sward height and calculates the available dry matter (DM) ha^{-1} using a conversion equation. The herbage density differs among grassland usage, herbage composition and geographical regions. Therefore, we tested the Grasshopper® in Switzerland and Denmark and compared the herbage quantity estimations with laboratory results. We collected fresh herbage samples at four locations in Switzerland and at three locations in Denmark during summer and autumn 2018. The samples were oven-dried at 60 °C and the quantity of DM ha^{-1} was calculated. The results indicate a more correct herbage quantity estimation of the Grasshopper® with its original equation for Danish pastures compared to Swiss grassland. As a conclusion, we suggest implementing region-specific herbage density estimations and known seasonal quality changes for the Grasshopper®.

Keywords: Grasshopper®, rising plate meter, pasture management, real-time measurement

Introduction

The utilisation of the amount of feed on pastures can only be optimised if it is quantified properly. In many countries where pasture-based dairy production is not yet widespread or farms have site-specific limits of intensification, farmers usually estimate forage quantity by visual observation. This method is prone to error. Moreover, a big challenge is not only the sward height estimation but also the constantly changing forage quality within the vegetation period. Hence, to be able to manage pasture precisely, we need to automate herbage quantity and quality measurements in real-time in the field, at low costs and with management tools that support farmers' decision-making.

Sward height measurements are commonly performed using rising plate meters (RPM, e.g. Jenquip, Feilding, New Zealand) in high pasture, grassland-rich countries, such as New Zealand and Ireland, and are therefore considered to be the "method of choice". Subsequently, standard equations to convert compressed sward height measurements into feed quantity estimates are used. Previous studies have shown that the conversions may vary considerably between geographical regions and between seasons (Schori *et al.*, 2013; Defrance *et al.*, 2004). MacAdam & Hunt (2015) pointed out that the correct conversion is also affected by plant species growing on the pasture. The authors recommend using specific conversion factors for different species. This is not always applicable because grasslands often consist of mixtures of species. There is the possibility to create one's own conversion equation to determine dry matter quantity within a paddock that represents the farm or even field specific conditions. However, this method would be relatively complex and laborious for farmers. Furthermore, for intensive grazing systems, determining the allocated paddock size is of importance.

A further development of RPMs is the combination of herbage quantity linked to the georeferenced location of compressed sward height (CSH) measurements (Grasshopper®, G2 Sensor, TrueNorth Technologies, Shannon, Ireland). The Grasshopper® is able to predict the available feed and provides a paddock management tool on a mobile device, in combination with a cloud based database that allows farmers in field decision making. Additionally, the Grasshopper® acts as a decision support system by using its feed calculation tool to reset fences for grass allocation. In this regard, the system has to be reliable in estimating herbage quantity on pastures.

While McSweeney *et al.* (2018) found the ultra-sonic method of the Grasshopper® to be accurate in grass height measurement. There is very little research on the accuracy of herbage quantity estimations of the Grasshopper® system applicable for Swiss and Danish grasslands. Therefore, we evaluated the commercially available system.

Material and methods

Experimental design

Herbage was sampled at four locations in Central Switzerland with three replicates each at two observations, counting 24 in total. The same procedure was performed at three locations in Denmark with 20 observations in total during summer and autumn 2018. Due to a severe drought in Switzerland two observations are missing, leading to a total of 42 Grasshopper® observations (Table 1). The locations differed in altitude and herbage composition, considering that they represented permanent grassland and temporary ley in parts for Switzerland and permanent pastures for Denmark. All experimental plots in Switzerland were managed in order to simulate a grazing situation with an average pasture growth of two weeks.

In Denmark, the Grasshopper® measurements were performed on six fields with an area of 4.2–7.6 ha, whereas the experimental plots in Switzerland had an area of 2.2 m times 5 m. An unvegetated border of approximately 15 cm width surrounded these plots (Figure 1).

Sensor technology and usage

The Grasshopper® system is a partly automated RPM. It represents an RPM with a mounted sensor that recognises the distance of plate lift and is able to georeference each measurement with an integrated GNSS-receiver module. The sensor is connected to a mobile device via Bluetooth and visualises the measurements in the Grasshopper® App (Version 3.03).

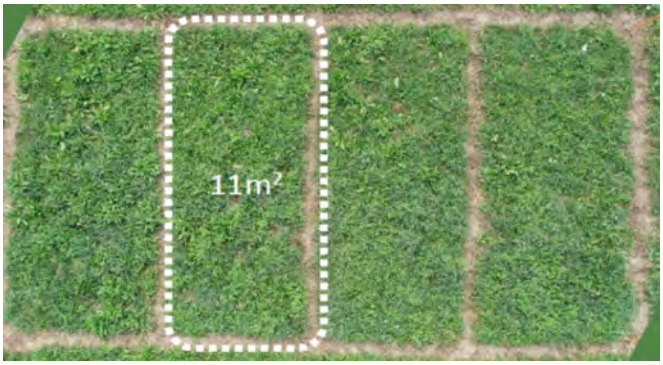

Figure 1. The present study is part of a larger experiment in Switzerland. One of the experimental plots of interest is shown here (marked plot)

Table 1. Description of experimental sites, observations, and available Grasshopper® samples

Experimental site & country		Altitude (m, above sea level)	Observation date	No. of sampled plots / fields
Malters Tal	CH	470-480	18 Jul. 2018	3
			28 Aug. 2018	3
Malters Berg	CH	680-690	6 Aug.2018	1
			13 Sept. 2018	3
Schwarzenberg	CH	880-910	6 Aug. 2018	3
			13 Sept. 2018	3
Sigigen	CH	780-800	7 Aug. 2018	3
			14 Sept. 2018	3
Farm 40167	DK	25-100	29 Aug. 2018	1
			6 Sept. 2018	1
			12 Sept. 2018	2
			19 Sept. 2018	3
			26 Sept. 2018	2
			3 Oct. 2018	3
Farm 24029	DK	25-100	29 Aug. 2018	1
			6 Sept. 2018	2
			12 Sept. 2018	2
Farm 26279	DK	25-100	29 Aug. 2018	1
			6 Sept. 2018	1
			12 Sept. 2018	1

Using the Grasshopper® system, we measured the geolocation of each corner in order to map the experimental plot (Figure 1) and fields. Subsequently, we randomly took samples within each area using the Grasshopper®. The system asked to input dry matter (DM) content and a value for the post-grazing sward height residual. The pre-settings were defined as follows: 25% DM content and 50 mm post-grazing residual for Switzerland, and 17% DM content and zero mm post-grazing residual for Denmark.

During the sampling, the Grasshopper® App recorded CSH measurements in real-time and calculated the available feed quantity within the defined area (DM kg ha^{-1}). To evaluate the accuracy of the Grasshopper®, its estimates were compared to laboratory measurements that were based on cutting fresh herbage samples in the field.

Fresh herbage sample collection

From each Swiss experimental plot, one square metre was cut at 50 mm above ground. In Denmark, three quadrats of herbage were randomly cut in each field at 40 mm above ground and fresh weight was determined. Following this, the samples were oven-dried in the laboratory at 60 °C, weighed and the DM content as well as the DM ha^{-1} was calculated and assumed as gold standard method, referred to as laboratory measurements.

Data analysis

The herbage quantity determination in the laboratory were compared to the Grasshopper® estimations for Swiss and Danish grasslands. No conversion calibration was done for the system, because we wanted to detect the standard equation of the system. Therefore, the measured CSH were plotted against the estimated herbage quantity. Following this, the conversion equation was derived through regression analysis.

Results and discussion

The amount of herbage on Danish pastures was generally higher than in Switzerland. Figure 2 shows that the Grasshopper® detected these differences with its original conversion equation for estimating DM ha^{-1}. The system tended to overestimate herbage quantity on Swiss grasslands. This could be caused by differences in the herbage composition of both countries. Another reason is that for Denmark, laboratory samples were cut at 40 mm above ground but the post-grazing residual was set to zero mm, because pre-tests on Danish pastures showed that the pre-setting of zero mm of post-grazing residual resulted in best estimates for herbage quantity during September.

Further, the correlation between the Grasshopper® estimates for herbage quantity and the laboratory measurements indicate differing results. The Swiss data resulted in a Pearson correlation coefficient of $r = 0.57$ while the Danish data correlate with $r = 0.77$. According to Taylor (1990), such correlation coefficients can be interpreted as weak for Swiss data and moderate for Danish data. The Grasshopper® has a standard error of prediction (SEP) of 100.1 DM kg ha^{-1} for Swiss data and a slightly better SEP of 79.7 DM kg ha^{-1} for Danish data.

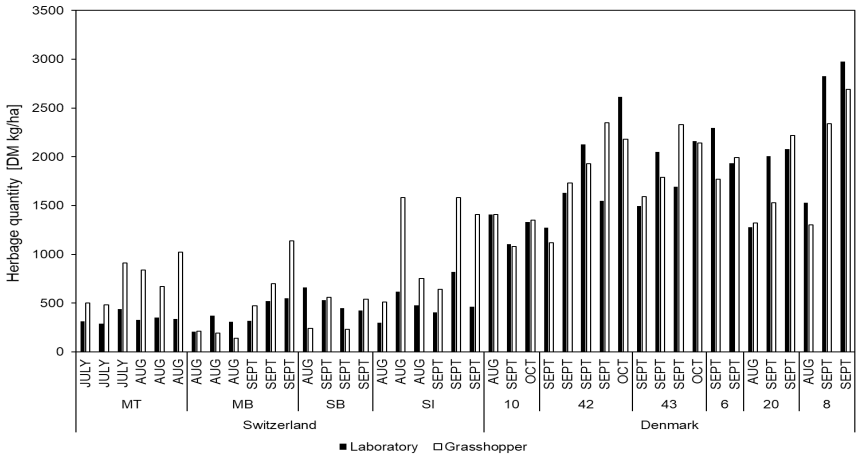

Figure 2. Comparison of dry matter quantity (DM kg ha^{-1}) on pastures estimated by Grasshopper® and measured by cutting and weighing, referred to as laboratory measurements. Field identifications are abbreviated as: Malters Tal, MT; Malters Berg, MB; Schwarzenberg, SB; Sigigen, SI; Farm 40167 includes Fields 10, 42 and 43; Farm 24029 includes Fields 6 and 20; Farm 26279 includes Field 8

Figure 3 shows compressed sward heights plotted against herbage quantity and the conversion equations that have been used by the Grasshopper® and the laboratory. The Grasshopper® conversion equations showed a linear relation and differed for Swiss and Danish conditions:

- $y = 38x - 1765$ for Switzerland (1)
- $y = 27x - 1017$ for Denmark (2)

where y is dry matter in kilograms per hectare and x is CSH in cm.

Contrarily, the laboratory measurements resulted in different equations to explain the relation between CSH and the actual amount of DM:

- $y = 5.9x + 59$ for Switzerland (3)
- $y = 24x - 628$ for Denmark (4)

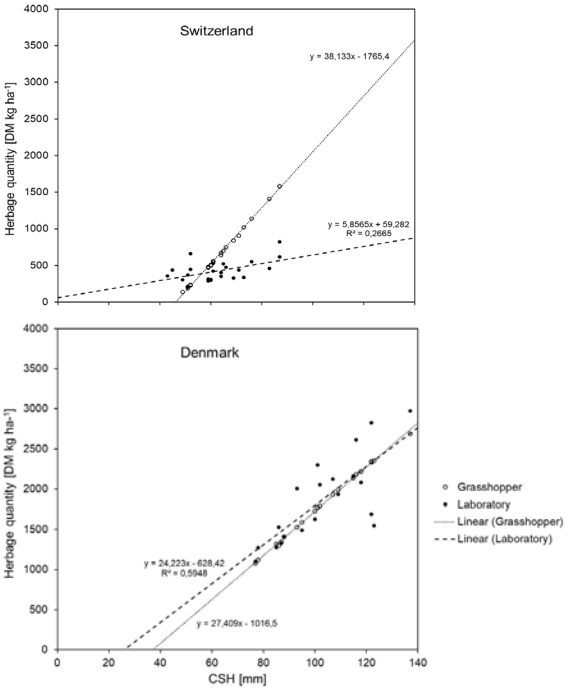

Figure 3. Compressed sward height (CSH) plotted against herbage quantity. The regression lines show the conversion equations used by the Grasshopper® system (dotted line) and the dashed line that explains the laboratory measurements

For Danish grasslands, the Grasshopper® estimate is close to the equation based on laboratory measurements. For Switzerland, where we measured lower sward heights, the estimation of herbage quantity differed strongly with the laboratory measurements. One reason may be that the Irish growth conditions, on which the Grasshopper® is based, are more similar to Danish conditions than to Swiss conditions. However, the conversion equations could also differ because of the pre-settings that we made in the Grasshopper® App before taking the measurements. The equations above are derived from the pre-setting of 25% and 17% DM content as well as 50 mm and 40 mm post-grazing residual for the Swiss and Danish data, respectively. We suggest analysing the data further in order to correct the defined value for DM content.

The findings demonstrate the need to adapt the DM quantity estimations for different regions. The accuracy of the Grasshopper® system may be better for taller swards or grass-rich locations. However, the analysis needs to account for different proportions of herbs and clover at different locations. In the field, users of the Grasshopper® should have the option to adapt the algorithm according to herbage density and herbage composition. For example, Skovsen *et al.* (2017) developed an App that detects the proportion of clover,

grasses and herbs due to image analysis after taking a photo in the field. For Switzerland, Schori *et al.* (2013) developed equations to convert RPM measurements into herbage quantity depending on grassland usage and the proportion of herbs. In a next step, we should check if the conversion equations of Schori *et al.* are more accurate than the Grasshopper® equations in estimating herbage quantity. Additionally, the Grasshopper® has to be evaluated during spring and early summer.

Conclusions

The Grasshopper® estimated the DM quantity more accurately on Danish grasslands than on Swiss grasslands. For diverse Swiss grasslands the system is not yet sufficiently precise to rely on it for pasture allocation decisions. At this point, it cannot substitute for visual observations and experience of farmers to determine the available feed on pastures in regions with diverse species composition. In areas with more defined grass-rich species, the Grasshopper® has the benefit of being a rapid and user-friendly system.

Hence, there is considerable potential for the Grasshopper® in supporting pasture allocation and feed ration balancing if there is a possibility to combine it with farm-specific measurements, possibly with implementing clover and herb proportions of pastures and areas where feed losses have occurred.

Acknowledgements

This EU project called GrassQ: *Development of ground based and remotes sensing, automated 'real-time' grass quality measurement techniques to enhance grassland management information platforms* is funded by ICT-Agri Era-Net. We gratefully acknowledge the national funding of FOAG, Switzerland and the Danish funding agency.

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References

Defrance, P., Delaby, L. and Seuret, J.M. (2004). Contribution to a better knowledge of sward density, a parameter useful to calculate grass growth, pasture biomass and farm cover. *Renc. Rech. Ruminants,* 11: 291–294.

MacAdam J.W. and Hunt, S.R. (2015). Using a rising plate meter to determine paddock size for rotational grazing. *AG Forages,* 2015–01.

McSweeney D., Coughlan, N.E., Cuthbert, R.N., Halton, P., and Ivanov, S. (accepted 2018) Micro-sonic sensor technology enables enhanced grass height measurement by Rising Plate Meter. *Information Processing in Agriculture,* https://doi.org/10.1016/j.inpa.2018.08.009.

Schori, F. (2013). Die Wuchshöhe von Weiden und Wiesen messen. *ALP aktuell*, Agroscope Liebefeld-Posieux.

Skovsen, S., Dyrmann, M., Mortensen, A.K., Steen, K.A., Green, O., Eriksen, J., Gislum, R., Jorgensen, R.N., and Karstoft, H. (2017). Estimation of the botanical composition of clover-grass leys from RGB images using data simulation and fully convolutional neural networks. *Sensors,* 17: Basel.

Taylor, R. (1990). Interpretation of the correlation coefficient: a basic review. *Journal of Diagnostic Medical Sonography,* 6: 35–39.

Dry Mater yield evaluation of grass varieties on commercial farms

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Abstract

Conventional perennial ryegrass evaluations are conducted under simulated grazing studies to identify varieties with the highest dry matter production performance. The objective of this study was to evaluate the DM yield performance of a range of perennial ryegrass varieties on commercial farms. Monocultures of 11 Irish National Recommended List perennial ryegrass varieties were sown on 89 commercial farms throughout Ireland where performance was evaluated over a five year period from 2013–2017, inclusive. A linear mixed model was used to test variety effects on grassland performance characteristics. There was a significant ($P < 0.001$) effect of variety on total and grazing DM yield. The results of this study show that on-farm evaluation can be an effective way to evaluate the DM yield performance of varieties in intensive grazing regimes.

Key words: Monocultures, yield, variety, on-farm assessment, DM (dry matter), phenotypic performance

Introduction

Grass evaluation programmes capable of identifying superior grazing varieties are essential to the success of ruminant production in Ireland. Ireland's temperate climate gives rise to a natural ability to grow grass throughout most of the year. This creates a competitive advantage because of relatively low production costs, since ruminant production systems are able to utilise high levels of grass. This ability is hugely beneficial as grass, particularly grazed grass, is of high nutritive value and is the cheapest feed source available to Irish production systems. A 10% increase in the proportion of grazed grass in the overall diet of a dairy cow will reduce the cost of milk production by €0.025 per litre (Dillon *et al.,* 2005). Irish grasslands have the potential to grow between 12–16 t/ha of grass dry matter (DM) annually. The removal of European milk quotas has resulted in the expansion of the Irish dairy industry. Increasing grass growth and utilisation at farm level is imperative to the success of such developments. With increased market volatility for milk, beef and inputs, such as fertilizer and concentrates, the profitability of ruminant grazing will be dependent on increasing the proportion of grazed grass in animal's diet.

An evaluation process to identify and promote the use of new varieties with improved on-farm performance in the areas of production, persistence and quality is necessary to increase the profitability and due to the economic importance of ruminant grazing systems. Since the introduction of Recommended List evaluations to Ireland, the grassland demands of farmers have changed. The question remains whether current evaluations provide breeders with adequate selection criteria and feedback to develop new grass varieties which are consistent with the needs of grassland farmers. To overcome the limitations of simulated grazing studies and identify superior grass genotypes suited to grazing systems, there is a need to establish trials which better simulate 'commercial' farm conditions for longer periods than current evaluation protocols. On-farm evaluation has the ability to influence and redirect the breeding of the next generation of grass varieties suited to intensive grazing regimes. The objective of the current study was to investigate the DM production performance of grass varieties on-farm within grazing regimes in Ireland. The current study presents results from the first five years of the study.

Materials and methods

PastureBase Ireland (Hanrahan *et al.,* 2017) is a web-based grassland database which has a dual function of providing real time decision support for farmers while acting as a national grassland database, capturing information for benchmarking and research purposes. This was a longitudinal study of grass performance on 637 paddocks across 89 grassland farms during the period January 2013 to December 2017. Farms which varied in regions on differing soil types operating grass-based spring calving herds were identified and enrolled. Within PBI the drainage characteristics of each paddock were also categorised. A range in pH across all farms was noted with a pH average of 6.30 operating at between 170–250kg N/ha/yr. across paddocks with an additional allowance of 250kg of inorganic N/ha/yr.

PastureBase Ireland (PBI) (Hanrahan *et al.,* 2017) is a web-based grassland database which has a dual function of providing real time decision support for farmers while acting as a national grassland database, capturing information for benchmarking and research purposes. The system operates with the individual farm paddock (experimental unit in the current study) as the basic unit of measurement. All grassland information is recorded by the farmer through the web interface. Recorded data must satisfy predefined verification rules programmed into the system. Such verification checks include restrictions on grass cover estimations (0–3,500 kg DM/ha), silage yields (0–10,000 kg DM/ha) and residual heights (2.5–9.0 cm). All measurements on PBI are described and calculated on a per hectare basis for individual paddocks. The operator builds a profile for each paddock, entering background information such as size, distance from parlour (dairy operators only), altitude, aspect, drainage status, reseed date and method, sown varieties and soil fertility records. Throughout each of the years, all participating farmers were provided with grassland management training to ensure data was recorded correctly and coherently and that management practices were adhered to, in order to test varieties sufficiently and to disseminate new information. All farmers were members of a farmer discussion group, which meet on a monthly basis during the main grazing season. The varieties sown were all listed on the Department of Agriculture, Food and Marines Recommended grass variety list (2015). The varieties Pasture Profit Index values and sub-index values are shown in Table 1.

Grass varieties were sown in monoculture in individual paddocks from 2011–2015 on all of the 89 commercial farms according to stringent guidelines which ensured successful sward establishment. All paddocks for reseeding were sprayed with Glyphosate to ensure that all botanical species were removed. Surface trash was removed pre cultivation. A range of cultivation methods were used to form a fine and firm seed bed. When a suitable seed bed was achieved, varieties were sown at a seeding rate of 34.5kg/ha. Chemical N, P and K were applied at the time of sowing. Varieties with a range in heading dates were selected and all farms are allocated tetraploid and diploid varieties. Grass DM production was measured 1 January to 31 December, annually. Grazing and silage DM yields were assessed prior to grazing or harvest and were recorded in PBI. The effect of variety on DM production was estimated using a mixed linear model in PROC MIXED (SAS inst. Inc., Cary, NC, USA) with paddock nested within farm included as a repeated measure with a compound symmetry covariance structure assumed among paddocks within a farm.

Table 1. Pasture Profit index values (2015) of varieties used on farms

Variety	Details		Pasture Profit Index			Sub Indices	€/ha/ year		
	Ploidy	Heading date	Spring	Summer	Autumn	Quality	Silage	Persistency	Total €/ ha/year
AberGain	T	June 5	42	50	43	58	26	-11	208
Dunluce	T	May 30	43	45	58	35	24	-11	194
AberChoice	D	June 10	24	52	47	57	9	-5	184
AberMagic	D	May 30	47	53	78	21	13	-28	184
Kintyre	T	June 8	29	40	58	25	14	0	166
Astonenergy	T	June 2	10	41	43	54	12	0	160
Drumbo	D	June 7	27	35	35	36	-4	-11	118
Majestic	D	June 2	43	38	43	-23	0	0	101
Glenveagh	D	June 3	37	39	34	-22	7	0	96
Twymax	T	June 7	-11	48	20	27	17	-5	95
Tyrella	D	June 4	41	23	19	-1	0	-11	71

Table 2. DM yield (kg/ha) and Standard error of varieties of perennial ryegrass on commercial farms over five years (2013–2017)

	Year 2013	Year 2014	Year 2015	Year 2016	Year 2017	Mean
AberChoice	13,450 - 691	12,533 - 590	13,985 - 589	14,431 - 555	14,563 - 498	13,811 - 377
AberGain (T)	12,784 - 716	15,133 - 548	15,422 - 555	15,137 - 405	15,593 - 360	14,846 - 328
AberMagic	11,437 - 887	13,670 - 860	13,180 - 863	16,093 - 937	16,047 - 940	14,081 - 603
Astonenergy (T)	12,822 - 503	14,713 - 496	15,233 - 500	15,077 - 478	14,724 - 448	14,509 - 319
Drumbo	13,096 - 645	15,046 - 591	14,160 - 556	15,124 - 552	15,241 - 526	14,550 - 376
Dunluce (T)	10,951 - 783	13,535 - 618	13,176 - 562	14,204 - 507	16,019 - 513	13,585 - 392
Glenveagh	11,311 - 922	13,876 - 754	13,533 - 686	13,242 - 577	14,813 - 547	13,382 - 444
Kintyre (T)	13,555 - 546	13,428 - 488	14,372 - 505	13,632 - 522	14,342 - 501	13,874 - 336
Majestic	12,036 - 945	13,829 - 733	13,014 - 722	13,608 - 651	15,572 - 632	13,640 - 480
Twymax (T)	12,634 - 647	13,774 - 492	13,498 - 468	14,673 - 471	14,746 - 500	13,869 - 327
Tryella	12,915 - 379	13,204 - 345	13,347 - 343	13,823 - 352	14,422 - 394	13,541 - 236

*(T) – indicates a tetraploid variety. All other varieties are diploid

Results and discussion

There was a variety × year interaction ($P < 0.001$) for total and the grazing DM yield. There was a significant ($P < 0.001$) effect of variety on total and grazing DM yield. The highest performing variety for total DM yield was AberGain (14,846 kg ± 328kg) and the lowest yielding variety was Glenveagh (13,382kg ± 444kg). The highest yielding variety with respect to grazing DM was AberGain (12,600 kg ± 394) and the lowest yielding variety was Dunluce (10,555 kg ± 476kg). The current study challenges the grassland industry to embrace new methodologies to quantify the commercial DM performance of grass varieties at industry level. The introduction of PBI (Hanrahan *et al.,* 2017) and the use of routine grass measurement at farm level introduces new innovations to grassland research, allowing more added value to grassland research benefiting farmers and the wider industry. This study presents the first five years of a long-term study assessing the performance of varieties on commercial farms. This methodology adds a new dimension to grassland research, by determining if the gains in grass breeding have reached farm level. The current study investigated a much wider array of environments and included each province of Ireland, resulting in a larger production range from approx. 6,500–19,500 kg DM/ha between paddocks across farms. The wide range in paddock management, soil fertility and regional meteorological conditions contributed to the level of variation in on-farm herbage production. Grazing DM performance indicate how well a variety performs from a grazing perspective, with more frequently grazed swards having greater DM production. Previously (Byrne *et al.,* 2017) found grazing yield was to be a reliable indicator of the yield advantage of individual grass varieties due to a strong rank correlation between total and grazing performance of varieties estimated in the current study. The on-farm evaluated varieties were found to produce significantly different yields of grazed herbage. AberGain and Astonenergy achieved the highest yield of grazed herbage, combined with recording a low silage yield. Varieties such as AberGain, Drumbo, Twymax appeared to have good yield stability as their DM production increased year on year and maintained; the remaining varieties all experienced fluctuations in annual DM production. Longer time frames which allow swards to mature are required to assess DM yield stability.

Conclusion

Variety was found to have a significant effect on total herbage production on-farm, and grazing yield also differed by variety, the difference was 1.464 t DM/ha between varieties annually. This is important in identifying suitable varieties which will maintain and further enhance competitive advantage as a low-cost producer of animal derived proteins. Not only does the current study demonstrate the importance of on-farm varietal evaluation, but also it examines the value of a variety under an intensive grazing regime. Current and future developments in grass evaluations in Ireland need to result in the delivery of improved varieties suited to intensive grazing environments.

Acknowledgements

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References

Byrne, N. Gilliland, T.J., McHugh, N, Delaby, L. Geoghegan, A and O'Donovan, M. (2017). Establishing phenotypic performance of grass varieties on Irish grassland farms. *Journal of Agricultural Science,* DOI; 10.1017/S0021859617000740.

Department of Agriculture Food and the Marine (2015). Grass Variety Recommended list.

Dillon, P., Roche, J., Shalloo, L. & Horan, B. (2005). Optimising financial return from grazing in temperate pastures. In Utilisation of Grazed Grass in Temperate Animal Systems (Ed. J.J. Murphy), pp. 131–147. Wageningen, the Netherlands: Wageningen Academic Publishers.

Hanrahan, L., Geoghegan, A., O'Donovan, M., Griffith, V., Ruelle, E., Wallace, M. & Shalloo, L. (2017). PastureBase Ireland: A grassland decision support system and national database. *Computers and Electronics in Agriculture,* 136: 193–201.

A preliminary near infrared spectroscopy calibration for the prediction of un-dried fresh grass quality

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Abstract

Near infrared spectroscopy (NIRS) is a well-established method of predicting the chemical constituents of a range of dried and milled forages. Limited research has been conducted on the application of NIRS to predict un-dried fresh grass quality. The aim of this study was to investigate the potential of NIRS to predict quality parameters, dry matter (DM, g kg^{-1}) and crude protein (CP, g kg^{-1}DM), in fresh un-dried grass. Knowledge of these parameters would enable more precise allocation of quality herbage to grazing livestock. Perennial ryegrass samples (n = 1,366) were collected over two grazing seasons at Teagasc Moorepark. Samples were scanned using a FOSS 6500 spectrometer at 2 nm intervals in the range of 1,100–2,500 nm and absorption was recorded as log 1/Reflectance. Reference analyses were carried out for both parameters and combined with the spectral data. A validation set (n = 205) was selected randomly and maintained separate from the original dataset. The remaining data were used to derive multiple prediction calibrations, by means of partial least squares regression using WinISI chemometric modelling software. A range of spectral treatments were investigated and calibrations were ranked in order of the highest coefficient of determination (R^2) and lowest standard error of cross validation (SE_{CV}). The best performing calibrations ($R^2 > 0.93$, $SE_{CV} < 9.40$ g kg^{-1} and $R^2 > 0.89$, $SE_{CV} < 13.1$ g kg^{-1}DM for DM and CP, respectively) were selected for further expansion and validation. Results indicate that it is possible to accurately predict fresh grass quality using NIRS.

Keywords: near infrared spectroscopy, fresh grass analysis, grassland management, grass quality, feed analysis

Introduction

Near infrared spectroscopy analysis measures the absorption rates of low energy infrared light radiation (700 nm – 2,500 nm) within matter, which are then used to quantify its chemical constituents by means of empirical modelling. It is a well-established method of rapidly analysing forage in the agri-food industry and has been proven to give precise predictions of quality parameters in agreement with wet chemistry analysis (de Boever *et al.*, 1995; Norris *et al.*, 1976). More recently, NIRS grass quality prediction calibrations have been derived for research purposes, such as identifying desired traits for the purpose of breeding grass varieties (Burns *et al.*, 2012; Jafari *et al.*, 2003; Wilkinson *et al.*, 2014). Conventional NIRS forage and grass analysis requires time consuming pre-processing of samples such as grinding and drying, which also can have detrimental effects on sample composition prior to analysis (Daniel *et al.*, 2003).

The development of rapid NIRS calibrations to predict quality of unprocessed fresh grass would not only significantly reduce laboratory labour, inputs and cost, but would further enable more precise grassland and feed management decisions to be made on a daily basis. Rapid and precise NIRS analysis of fresh grass would be of considerable practical benefit for grass based livestock industries. For example, on grass based dairy farms, the quality of grass can vary significantly throughout the year depending on factors such as climate, season and sward structure, which can affect milk yield and quality on a daily

basis (Dillon, 2006). Wilkinson *et al.* (2014) recommended that pasture samples should be analysed on a weekly basis to adjust feed and management decisions according to fluctuations in herbage quality.

Spectroscopic analysis of fresh forages and grasses is largely restricted by the high presence of moisture, which results in large spectral peaks that have been found to overshadow spectral identifiers for numerous quality traits such as CP (Deaville & Flinn, 2000; Feuerstein & Paul, 2007). Despite this, breakthroughs have been made with regard to NIRS analyses of fresh forage using conventional NIR instruments. A number of studies have highlighted the capabilities of NIRS to predict quality parameters of un-dried silage (Park *et al.*, 1998; Thomson *et al.*, 2018). Alomar *et al.* (2009) demonstrated how reflectance NIRS can accurately predict the compositional fractions of a variety of grass swards in Southern Chile. Dale *et al.* (2016) developed a NIRS calibration to investigate the impact of sampling and storage techniques on fresh grass composition.

The objective of this study was to investigate the potential for developing a NIRS calibration to accurately predict quality parameters of fresh grass to within an acceptable agreement with gold standard wet chemistry methods. This was to be achieved by developing preliminary NIRS calibrations to predict DM and CP, which is a factor of total nitrogen (N) content (N × 6.25). The results of this study will be used to justify the continuation of the calibration process to develop a robust NIRS grass quality prediction model that could be used by researchers and advisors to assist in day to day grassland and feed management decision making.

Material and methods

Sward Sampling

Grass samples (n = 1,366) were collected at the Teagasc Animal and Grassland Research Institute at Moorepark, Fermoy, Co. Cork, Ireland (50° 7´N, 18° 16´W), on predominately Perennial Ryegrass (*Lolium perenne*) monoculture swards between the period of January 2017 and October 2018. All swards were sown on free draining acid brown earth soil with a sandy loam texture. Herbage cuts were taken from grazed paddocks and controlled trial plots (5 m × 1.5 m) using an Etesia mechanical mower (Etesia UK Ltd. Warwick, UK). Sample cuts were typically taken in 5 m lengths to a height of 4 cm and the harvested herbage was weighed and subsampled (200 g) as in McEvoy *et al.* (2011). Sampling was conducted on a weekly basis throughout the typical Irish grazing season (late January - early November) to account for variations in climate and growth conditions. Cuts were taken prior to grazing on paddocks and typical rotation lengths varied from approximately 18–30 days depending on growth and seasonal conditions. Plot cuts (n = 16) were taken from four different control groups on a weekly basis with a regrowth period of 28 days between groups to simulate grazing conditions. Total annual N fertiliser applied to the paddocks was 250 kg N ha^{-1}, whereas the controlled plots were divided into four treatment groups, each receiving different N rates ranging from none to high (0, 119, 244, 480 kg N ha^{-1}).

Laboratory Analysis

To determine DM content for reference analysis, 100 g of each collected sample was oven dried at 60 °C at Moorepark's Grassland Research Laboratory. The remainder of each sample was then stored in a sealed bag and refrigerated for less than 48 h prior to spectral analysis, as recommended by Dale *et al.* (2016). Each sample was wrapped in cling film and packed into a large forage cell with a quartz screen and scanned using a FOSS 6500 spectrometer (FOSS-NIR System DK, HillerØid, Denmark). Scanning was carried out at 2 nm intervals in the range of 1,100 nm – 2,500 nm. Absorption was recorded as log 1/Reflectance and all data was stored in ISI Scan (ISI, Port Matilda, Pennsylvania, USA). Immediately after scanning all samples were re-sealed and frozen at -20 °C. Following this, the samples were bowl chopped

and then freeze dried over 48 h. All samples were then milled through a 1 mm sieve before entering storage. Reference CP figures were determined by further NIRS analysis of the dried and milled samples using a calibration developed by Burns *et al.* (2012).

Calibration Process

Box and whisker analysis was performed using R (R Core Team 2018) on the reference dataset along with a visual inspection of the NIR spectra to remove any extreme outliers (< 2%). All spectral and reference data was uploaded onto WinISI 4 (ISI, Port Matilda, Pennyslvannia, USA) for chemometric modelling. A validation set consisting of 15% (n = 205) of the original data was selected randomly and removed from the calibration dataset. Modified partial least squares was selected as the regression method and numerous spectral pre-treatments and mathematical treatments were evaluated on the calibration dataset. Principle component analysis was employed to detect outliers, which were removed on the basis of significantly high residual prediction values defined by critical T values > 2.5 and global H values > 10 as in Burns *et al.* (2012) and Alomar *et al.* (2009). A number of calibration models were derived and all model iterations were validated by means of cross validation using the initial validation set.

Results and discussion

Reference analysis figures for DM averaged 180 g kg^{-1} (range 95 – 345 g kg^{-1}) ± 38.70 g kg^{-1} (SD). Figures for CP averaged 208 g kg^{-1} DM (range 90 – 325 g kg^{-1} DM) ± 39.68 g kg^{-1} DM (SD). A partial drought occurred in Moorpark during the months of June and July 2018 (Met Éireann, 2018), which led to a number of abnormally high figures for DM, but did not have any adverse effect on the overall dataset. Over 20 NIRS model iterations were derived and evaluated for fresh grass quality analysis and the best performing models are presented in Table 1. Calibrations were ranked in order of the highest coefficient of determination (R^2) and lowest standard error of cross validation (SE_{cv}), as in similar studies (Alomar *et al.*, 2009; Reddersen *et al.*, 2013). All of the calibrations that included the spectral pre-treatments standard normal variate (SNV) and detrend performed better than those without. Detrend reduces the linear and quadratic curvature of each spectra, while SNV reduces partial size noise effects on the model by scaling each spectrum to have a standard deviation of 1.0. The effects of both pre-treatments are illustrated in Figure 1. The mathematical modelling treatment applied to each calibration, presented in the first column of Table 1, had the largest influence on performance. Each treatment is listed in the following order: derivative, gap, smoothing and second smoothing. Gap refers to the number of wavelengths over which the derivative is to be calculated and smoothing refers to level of fit of the function line. The second derivative was common amongst all of the best performing calibrations, while gaps of 8 nm and 6 nm appeared to give the best results. Smoothing applications appeared to have a less significant effect on model performance.

The mathematical treatment 2, 8, 6, 1 with spectral pre-treatments SNV and detrend, illustrated in Figure 1 (c) provided the best calibration performance. Results for this calibration indicated R^2 values of 0.941, 0.906 for DM and CP, respectively. The accuracies of these preliminary calibrations are comparable to results found by Alomar *et al.* (2009). With regard to CP, calibration accuracies were less than those found in studies for dried and milled grass by Burns *et al.* (2012) and Jafari *et al.* (2003). The authors acknowledge that prediction accuracy could be increased by creating a standalone calibration tailored specifically for CP, but this would further increase analysis time and laboratory labour. Furthermore, the authors note that using a NIRS equation for reference analysis of CP is not best practice and this was only used to derive the preliminary calibrations presented in this paper to determine the overall feasibility of creating a fresh grass quality prediction calibration. The inclusion of gold standard reference figures for CP in the reference dataset

may further increase prediction accuracies. All of the CP samples used in this study have been stored for further reference analysis in accordance with laboratory standards, to be used for future calibration work. The findings of this study illustrate that it may be possible to accurately predict fresh grass quality using NIRS. The work carried out in this study is scheduled to continue for the 2019 grazing season with the aim of completing a robust calibration to rapidly predict CP and DM in fresh grass.

Table 1. Best performing fresh grass NIRS calibrations

Math Treatment	Constituent	R^2	SE_{CV}
2, 8, 6, 1	DM	0.941	8.93
	CP	0.906	12.86
2, 6, 4, 1	DM	0.941	9.12
	CP	0.905	12.88
2, 6, 6, 1	DM	0.940	9.16
	CP	0.901	13.00
2, 5, 5, 1	DM	0.942	9.08
	CP	0.903	13.08
3, 8, 6, 1	DM	0.935	9.35
	CP	0.899	13.066

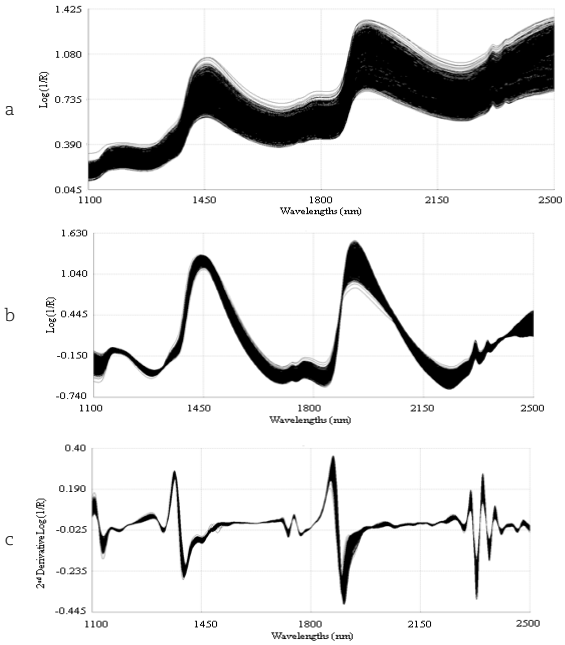

Figure 1. NIRS spectra - light reflectance/absorption vs NIRS wavelength; (a) untreated spectra, (b) SNV + Detrend treated spectra, (c) Spectra with mathematical treatment 2, 8, 6, 1 and SNV + Detrend

Conclusions

Preliminary NIRS calibrations were derived to predict fresh grass quality. Results from this study indicate that it is possible to accurately predict the DM and CP composition of fresh grass using NIRS, without the need for laboratory pre-treatments. A number of the calibrations included in this study were deemed sufficiently accurate to warrant further expansion and analysis. An NIRS fresh grass quality prediction equation would aid grass and feed management decisions and be highly beneficial to researchers, advisors and farmers.

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References

Alomar, D., Fuchslocher, R., Cuevas, J., Mardones, R. and Cuevas, E. (2009). Prediction of the composition of fresh grass pastures by near infrared reflectance or interactance-reflectance spectroscopy. *Chilean Jouranl of Agricultural Research,* 69: 198–206.

Burns, G., Gilliland, T.J., Grogan, D., Watson, S. and O' Kiely, P. (2012). Assessment of herbage yield and quality traits of perennial ryegrasses from a national variety evaluation scheme. *The Journal of Agricultural Science,* 151: 331–346.

Dale, A.J., Gordon, A., Archer, J. and Ferris, C. (2016). Impact of sampling and storage technique, and duration of storage, on the composition of fresh grass when analysed using near-infrared reflectance spectroscopy, 72: 1–12.

Daniel, A., Rita, F. and Marjorie, D.P. (2003). Effect of preparation method on composition and NIR spectra of forage samples. *Animal Feed Science and Technology,* 107: 191–200.

de Boever, J.L., Cottyn, B.G., Vanacker, J.M. and Boucqué, C.V. (1995). The use of NIRS to predict the chemical composition and the energy value of compound feeds for cattle. *Animal Feed Science and Technology,* 51: 243–253.

Deaville, E. and Flinn, P. (2000). An alternative approach for the estimation of forage quality and voluntary intake. In: D.I. Givens, E. Owen, H.M. Omed & R.F.E. Axford (eds) *Forage Evaluation in Ruminant Nutrition*, CAB International, Wallingford, UK, pp. 301–320.

Dillon, P. (2006). Achieving high dry-matter intake from pasture with grazing dairy cow. In: A. Elgersma, J. Dijkstra & S. Tamminga (eds) *Fresh Herbage for Dairy Cattle*, Springer, the Netherlands, pp. 1–26.

Feuerstein, U. and Paul, C. (2007). *NIR-spectroscopy of non-dried forages as a tool in breeding for higher quality - laboratory tests and online investigations on plot harvesters.* Paper presented at the European Association for Research on Plant Breeding, Copenhagen, Denmark, pp. 110–114.

Jafari, A., Connolly, V., Frolich, A. and Walsh, E.J. (2003). A Note on Estimation of Quality Parameters in Perennial Ryegrass by near InfraredReflectance Spectroscopy. *Irish Journal of Agricultural and Food Research,* 42: 293–299.

McEvoy M., O'Donovan, M. and Shalloo, L. (2011). Development and application of an economic ranking index for perennial ryegrass cultivars. *Journal of Dairy Science,* 94: 1627–1639.

Met Éireann (2018). Warm Dry Weather of June and July 2018, Met Éireann.

Norris, K.H., Barnes, R.F., Moore, J.E. and Shenk, J.S. (1976). Predicting Forage Quality by Infrared Replectance Spectroscopy1. *Journal of Animal Science,* 43: 889–897.

Park, R.S., Agnew, R.E., J Gordon, F. and Steen, R. (1998). The use of near infrared reflectance spectroscopy (NIRS) on undried samples of grass silage to predict chemical composition and digestibility parameters. *Animal Feed Science and Technology,* 72: 155–167.

Reddersen, B., Fricke, T. and Wachendorf, M. (2013). Effects of sample preparation and measurement standardization on the NIRS calibration quality of nitrogen, ash and NDFom content in extensive experimental grassland biomass. *Animal Feed Science and Technology,* 183: 77–85.

Thomson, A., Humphries, D.J., Rymer, C., Archer, J.E., Grant, N.W. and Reynolds, C. (2018). Assessing the accuracy of current near infra-red reflectance spectroscopy analysis for fresh grass-clover mixture silages and development of new equations for this purpose. Animal Feed Science and Technology 239: 94–106.

Wilkinson, J.M., Allen, J.D., Tunnicliffe, R., Smith, M. and Garnsworthy, P.C. (2014). Variation in composition of pre-grazed pasture herbage in the United Kingdom, 2006–2012. *Animal Feed Science and Technology,* 196: 139–144.

Evaluation of remote sensing technologies and cloud services to support grassland management

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Abstract

Remote sensing technologies, including new drone technologies, are developing rapidly and emerging onto the marketplace. These technologies may provide grass quality and quantity information to support grassland management. This concept was developed and evaluated in a collaborative research project (*GrassQ*) across four EU countries. In regions where silage forms a significant portion of cow diet, the timing of the first and subsequent silage cuts is critical. Monitoring of sward quality parameters, height and dry matter (DM), by drones/satellites can be used to identify the optimum harvest times. Alternatively, where pasture grazing systems are common, monitoring of herbage yield/mass is critical to optimise precise herbage allocation to the herd. Drone and satellite technologies were used to capture this grass yield and quality over two growing seasons in Finland, Ireland, Denmark and Switzerland. A cloud based service and mobile application, allowing access and interpretation of these data was developed as a grassland management support tool. The prototype *GrassQ* management support system, incorporating drone and satellite data, analysis, modelling and visualisation tools, hosted on the cloud and application to provide Grassland information management service were presented to farmers in the different countries to evaluate in terms of usefulness, importance and robustness. This paper reports on the evaluation. Generally, satellite technologies were considered in a positive light, having the ability to streamline grassland management at farm level. Drone technology was considered as having potential to provide good yield estimates, while the application had potential to provide easy access to grassland management support information.

Keywords: Unmanned Aerial Vehicle UAV, Sentinel-2, Drones

Introduction

Managing pasture in dairy systems is a complex task; it involves matching fodder production to variable feed demands in a changing environment. Many of the decisions are influenced by events such as calving, opening and closing paddocks, and harvesting silage and hay for the winter. Optimising these decisions is one of the key drivers in ensuring a profitable farm, but this process can be difficult for the farmer. Grassland farmers are increasingly faced with an array of emerging new technologies and information systems, collectively termed Precision Farming (PF), that have been primarily developed around Remote Sensing, Unmanned Aerial Vehicle (UAV), in-situ sensors, Global Positioning System (GPS) and GeoInformatics (Schellberg and Verbruggen, 2014). Especially these remote sensing technologies, including drone and satellite technologies are developing rapidly and emerging onto the marketplace. There are Sentinel-2 based web cloud services such as *Cropsat, MyYara, WebWisu, AgriSmart* that provide farmer specific data. Some of them are free to the user and some are integrated into the farm management system. In optimal cases, these technologies may provide grass quality and quantity information to support grassland management.

In regions where silage forms a significant portion of cow diet, the timing of the first and subsequent silage cuts is critical. Monitoring of sward quality parameters, height and dry matter (DM), by drones/satellites can be used to identify the optimum harvest times. Alternatively, where pasture grazing systems are common, monitoring of herbage yield/mass is critical to optimise precise herbage allocation to the herd.

However, actual implementation and sustainable operation is not without its shortcomings. Issues such as cloud cover affecting satellite Remote Sensing (Whitcraft *et al.,* 2015), sensor calibration, operational restrictions of UAVs and subsequent data handling workflows still present some challenges (von Bueren *et al.,* 2015) and even small changes in sensor outputs could have a considerable effect on the final application (Pena-Yewtukhiw *et al.,* 2015).

In a collaborative research project *GrassQ*, drone and satellite technologies were used to capture grass yield and quality with different and partly new methodologies in Finland, Ireland, Denmark and Switzerland. A cloud based service and mobile application, allowing access and interpretation of these data was developed as a grassland management support tool. This *GrassQ* management support system incorporates drone and satellite data, analysis, modelling and visualisation tools and is hosted on the cloud and application to provide Grassland information management service.

This study is focused on sketching out the user needs in the near future. The main research question was: how farmers consider future remote sensing based applications in grassland management? We presented the *GrassQ* prototype and a set of remote sensing application concepts for grassland management to farmers, researchers and stakeholders in the different countries to evaluate them in terms of usefulness, importance and robustness in an informal way. In this paper we present the concepts and the evaluation results.

Material and methods

First we compiled different relevant remote sensing applications and the constructed grassland management platform prototype and then we evaluated them by means of a survey questionnaire and free discussions in the different countries.

Remote sensing applications

There were five main remote sensing applications to be considered.

- Relative grass biomass estimations based on drone data (Figure 1a). This is perhaps the most common means by which drone data is utilised in agriculture. A simple map shows detailed variation within a paddock. In this case it shows the variation in grass biomass. This map can be used as support data for manual decision making.
- Relative grass biomass estimations based on classified satellite imagery (Figure 1b). This is the most common practice. Typically a straight NDVI calculation represents the difference between red light and near infrared light revealing the greenness difference which correlates well with biomass differences.
- Absolute grass biomass estimations based on drone data (Figure 1c). This is a new approach developed during the *GrassQ* project. The focus here is that the mapping process could provide usable information for the decision support systems. Manual data capture and manual data analysis and decision making would not be necessary. Direct biomass is assessed by two-step hyperspectral methods (Ancin-Murguzur *et al.,* 2019) and by spectral and 3D-modelling integration (Näsi *et al.,* 2018a, Näsi *et al.,* 2018b, Viljanen *et al.*, 2018).
- Grass quality estimations based on drone data (Figure 1). The biomass differences are important for grazing but knowledge of the digestibility variations can be considered

equally important in silage production. A logical step would be a smart combination of biomass and digestibility maps. Publications related to grass quality are currently under review.

- Field biomass and quality comparisons based on satellite imagery (Figure 1e). Maps can compare paddocks with relative differences in biomass and quality. This is an application area where drones have difficulties in competing with satellites. Satellite images can cover wide areas thus a single dataset may easily cover fields of an entire farm. This makes it possible to compare different fields. Combining different drone campaigns is possible but the changing illumination conditions make the true comparison somewhat difficult. The relative value can be a mean value of NDVI's within a field. In *GrassQ*, pixels closer than 10 m to the field borders were not considered. This was applied to eliminate most of the forest/building shadowed pixels and the areas that were weakened because of field traffic (headland areas).

Grasslands Management Platform

The GrassQ.org scalable Grassland Management platform was configured and adapted in four EU States. The following elements were considered in the Grasslands Management Platform:

- Cloud-based platform and Open Source Software and database technologies
- Secure account and farm-project management system
- Design and implementation modules for all data handling aspects; ingestion, storage, discovery, fusion, analysis, visualisation and reporting
- Provision of Web Services and also a Grassland Platform AP
- Interoperability (OGC, ISOBUS)
- Country-specific calibration procedures

The platform provides timely information to farmers using the tools through either Smartphones or mobile devices.

Evaluations

A thorough evaluation of a specific application or service may be difficult as technologies and applications develop so rapidly. So an internationally coordinated questionnaire based on one developed system may not provide up-to-date and useful information. Instead, several concepts and prototypes operating in different scenarios were introduced to farmers, researchers and stakeholders in order to have an up-to-date full picture of the topic.

The different remote sensing application concepts and the Grasslands management platform were evaluated in terms of usefulness, importance and robustness in free discussions. In Finland, the discussions were performed at four main events; two *Nurmen Kasvun Paikka* events for milk producers, one annual dairy-coaching event and a national agri-drone seminar meeting with 250 people in attendance. In Ireland, the *GrassQ* service will be evaluated in the 'Grasslands Information Services' demonstrator project later in 2019. This demonstrator will focus on one farm in South-Western Ireland. These *In-Situ* data-streams will be merged with Remote Sensing and linked with the Teagasc PastureBase Ireland system to generate grassland management services. Local farming community groups will be involved in assessing these services.

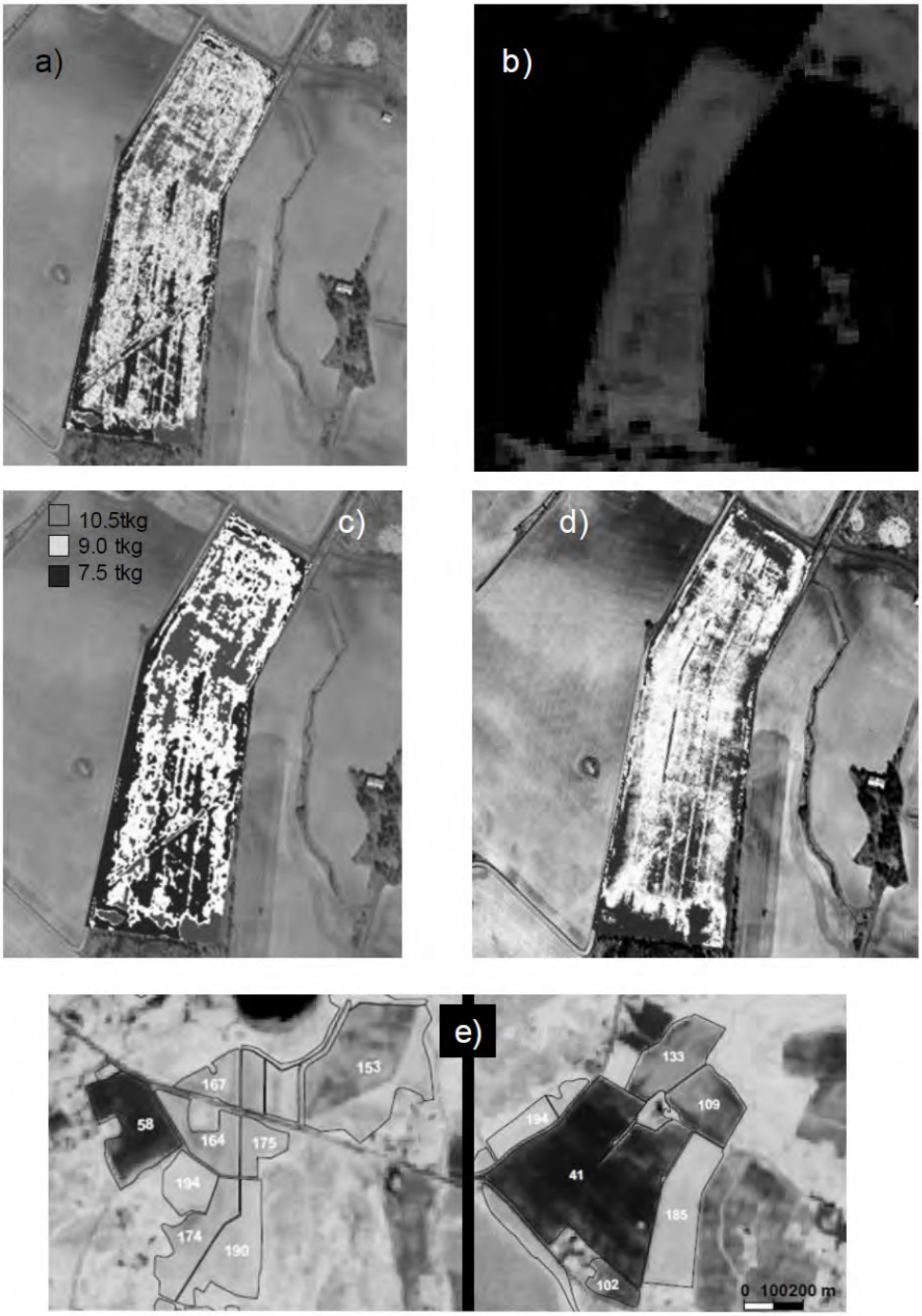

Figure 1. Examples of classified images for each application

Results and discussion

Generally, satellite technologies were considered in a positive light, having the ability to streamline grassland management at farm level. Drone technology was considered as having potential to provide good yield estimates, while the application had potential to provide easy access to grassland management support information.

The guiding information (such as relative values) was mostly observed in a twofold manner. Alternatively, these results can represent useful information, but its usefulness to the farmer is questionable since any concrete actions are not provided. This leads to the most important finding, that data should be applicable in a straight forward way. This means that the farmer interface does not need to show any relative NDVI values but it should have a direct decision support element. Examples may include decisions such as, 'harvest this area tomorrow and you get 5,000 kg DM/ha yield with good digestibility' or 'put the cattle next to that field'. This shows that smart decision support systems are needed.

The interviewed farmers were mostly willing to integrate all possible new technologies into their existing farm management systems. For example, they use a separate weather app to check the weather forecast and the integration of this with grassland management is considered feasible.

In Finland there was a desire to have a commercial grass biomass mapping application. It is considered a significant drawback that there are no widely spread grass yield mapping methodologies available. Also, the possibility to measure sugar content was seen to be beneficial in silage production since that information could be used to adjust preservative contents.

The main discussion topics of the evaluation

Usefulness: colourful maps or relative (within a field) values were not considered useful. Easy access application was seen as very useful. A separate PC web application with multiple folders and tabs was not seen as useful. An increase in the complexity was allowed in relation to increases in the compatibility with farm management and machinery. As a stand-alone solution, the simpler was always seen as best.

Importance: yield amount mapping and grass quality information were seen as very important. Data should be easily accessed and should not be ambiguous. The availability of source data or transparent data processing was not observed as very important advice. However, the reliability of each piece of information is crucial. Obeying incorrect data was seen as a big risk.

Robustness: Passive remote sensing was not seen as being very robust. A lot of high risks were observed. Those included different grass varieties, different soil types and growing conditions, clouds in satellite images, drone data mosaicking, changing illumination conditions and over teaching in machine learning. The functioning robustness of the actual management platform was not evaluated.

Conclusions

The potential of remote sensing technologies in supporting grassland management has widely been recognised. Generally farmers are very keen on following the remote sensing application possibilities. However, the possible drawbacks are also well understood and most of the farmers are cautious on the utilisation of remote sensing applications.

Acknowledgements

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References

Ancin-Murguzur, F., Taff, G., Davids, C., Tømmervik, H., Mølmann. J. and M. Jørgensen.(2019). Yield Estimates by a Two-Step Approach Using Hyperspectral Methods in Grasslands at High Latitudes. *Remote Sensing,* 11: 400. Doi:10.3390/rs11040400.

Hedley, C. (2015). The role of precision agriculture for improved nutrient management on farms. *J. Sci. Food Agric.,* 95: 12–19. doi:10.1002/jsfa.6734.

Nikander, J., Huitu, H., Koistinen, M., Laajalahti, M., Niemeläinen, O., Kaivosoja, J. (2018). Application of Drone-Based Maps in Planning Farm Operations for Sward Management in Silage Production. *European Society of Agricultural Engineers (EurAgEng)* Wageningen 7 p.

Näsi, R., Viljanen, N., Kaivosoja, J., Alhonoja, K., Markelin, L., Honkavaara, E. (2018a). Estimating Biomass and Nitrogen Amount of Barley and Grass Using UAV and Aircraft Based Spectral and Photogrammetric 3D Features. *Remote Sens.* 2018, 10(7), 1082. https://doi.org/10.3390/rs10071082.

Näsi, R., Viljanen, N., Oliveira, R., Kaivosoja, J., Niemeläinen, O., Hakala, T., Markelin, L., Nezami, S., Suomalainen, J., and Honkavaara, E. (2018b). Optimizing radiometric processing and feature extraction of drone based hyperspectral frame format imagery for estimation of yield quantity and quality of a grass sward. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci., XLII-3, 1305-1310, https://doi.org/10.5194/isprs-archives-XLII-3-1305–2018.

Pena-Yewtukhiw, E., Grove, J., Schwab, G. (2015). Fertilizer Nitrogen Rate Prescription, Interpretational Algorithms, and Individual Sensor Performance in an Array. *Agron. J.* 107:1691–1700. doi:10.2134/agronj14.0573.

Schellberg, Jürgen & Verbruggen, Erik. (2014). *Frontiers and perspectives on research strategies in grassland technology. Crop and Pasture Science,* 65: 508–523. 10.1071/CP13429.

Viljanen, N., Honkavaara, E., Näsi, R., Hakala, T., Niemeläinen, O., Kaivosoja, J. (2018), *A Novel Machine Learning Method for Estimating Biomass of Grass Swards Using a Photogrammetric Canopy Height Model*, Images and Vegetation Indices Captured by a Drone, Agriculture 2018 8 (5). http://dx.doi.org/doi:10.3390/agriculture8050070.

von Bueren, S.K., Burkart, A., Hueni, A., Rascher, U., Tuohy, M.P., and Yule, I.J. (2015). *Deploying four optical UAV-based sensors over grassland: challenges and limitations*. Biogeosciences, 12, 163-175, https://doi.org/10.5194/bg-12-163–2015.

Whitcraft, A.K.; Becker-Reshef, I.; Killough, B.D. (2015). Justice, C.O. *Meeting Earth Observation Requirements for Global Agricultural Monitoring: An Evaluation of the Revisit Capabilities of Current and Planned Moderate Resolution Optical Earth Observing Missions.* Remote Sens, 2015(7): 1482–1503.

Session 6

Precision Livestock Farming Technology for Milking of Dairy Animals

Prospects for precision milking management in automatic milking systems

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Abstract

This paper presents an analysis of the sources of variability in milk yield, milking time and milking interval of cows with voluntary access to a quarter milking Automatic Milking System (AMS). The data used for this analysis included a large data set from a commercial dairy farm using AMS technology. Multiple correspondence analysis and GLMselect were used to explore relationships between variables and select estimation models of the parameters that better identify milking efficiency. This analysis provides some theoretical limits and ranking of precision milking management strategies to improve the capital efficiency of AMS technology. The strategies identified in this analysis were: 1) Increasing the fraction of the day that the AMS box is occupied for milking; 2) Setting a minimum projected milk yield for milking permission; 3) Milking the slowest quarter faster; and 4) Reducing udder prep and attach time. Other substantial value-added propositions for AMS management are to improve the economics of feeding using cow level concentrate feeding and the use of economic models to identify less profitable cows as candidates for dry-off and culling.

Keywords: automatic milking, precision milking, economic efficiency

Introduction

One of the primary obstacles to implementing an Automatic Milking System (AMS) is the higher capital cost of the milking equipment and facilities compared to conventional milking technology. Studies have shown that reductions in labour costs are typically not sufficient to justify the additional capital investment (Schewe & Stuart, 2014). Increased milk production resulting from increasing milking frequency from twice daily milking provides some economic benefit (De Koning & Rodenburg, 2004), however, not when compared to 3x milking as is common on most large confinement based dairy farms. Other economic benefits attributed to automatic milking include improved animal health and increased cow longevity (Hamann, 2002; Stuart *et al.*, 2013) but it has been difficult to quantify the economic consequences of these factors. It appears that there are not large differences in milk quality or yield between cows milked by the robotic versus conventional milking system (Reinemann *et al.*, 2001).

The capital cost of AMS technology is largely balanced against the amount of milk harvested per AMS unit per day. The aim of this study was to explore associations between milking efficiency parameters to provide some theoretical limits on the milk harvested per AMS per day and identify precision milking management strategies to improve the AMS harvest rate and thereby the capital efficiency of AMS technology.

Material and methods

This study used data from one commercial dairy farm (n = 1,280 Holstein Friesian cows) using 20 AMS units (De Laval VMS, DeLaval, Tumba, Sweden) located in the Northeastern USA (more detail is provided by Penry *et al.*, 2018). This farm has used AMS technology for more than 10 yr. Cows are housed year-round and fed using a partial mixed ration system with concentrate feeding in the AMS stall. Each AMS services one pen of about 55 cows,

with 6 pens of primiparous cows (L1) and 14 pens of multiparous cows (L2+). The data obtained from the management system included Cow ID, DIM, start date:time of milking session, duration of the milking session, milk yield, peak milk flowrate and average milk flowrate at the quarter level, for each milking session. New variables were created to assess milking performance at the cow and AMS level. Definitions of the variables used in the analysis and the overall average and standard deviation values (for all cows and all AMS units over one year) are presented in Table 1.

Table 1. Variables, definitions and summary statistics of the dataset used in this analysis

	Mean ± std	**Units**
DIM: Cow level days in milk	162±111	days
Lact: Cow level lactation number	2.30±1.17	lactation
BoxTime: Time that a cow is in the AMS box for milking	6.99±2.22	min
UdderTime: Time to milk the udder = time for slowest Quarter*	4.14±1.75	min
LastQuarterTime: Difference between slowest quarter milking duration and next slowest quarter milking duration*	0.87±0.80	min
QuarterTimeSTD: Intra-udder standard deviation of quarter milking duration at each milking	0.75±0.54	min
BoxPrepTime = BoxTime –UdderTime	2.85±1.38	min
BoxMilkFraction = UdderTime /BoxTime	0.59±0.12	-
BoxAMF = UdderYield /BoxTime	1.79±0.61	kg/min
MilkingInterval: Time since last successful milking	8.46±3.39	hr
UdderYield: Sum of 4 quarter yields at each milking session	12.0±4.49	kg
MaxQyield= maximum quarter milk production	3.8±1.51	kg
QuarterYieldSTD: Standard deviation of within-udder quarter yields at each milking	0.74±0.58	kg
UdderFill: Ratio of UdderYield to lactation maximum UdderYield	0.52±0.17	-
UdderMPR: Milk production rate at the udder level, =UdderYield/ MilkingInterval	1.45±0.41	kg/hr
UdderAMF: Average milk flowrate at the udder level =UdderYield/ UdderTime	3.08±0.97	kg/min
UdderPMF: Udder level peak milk flowrate sum of quarter peak milk flowrates	5.66±1.36	kg/min
UdderAmfPmf = Udder AMF/UdderPMF	0.54±0.08	-
BoxTimeSum: Total box time usage per day	16.9±1.69	hours

* UdderTime and LastQuarterTime are approximations that do not take into account teatcup attachment order

Class variables were created to perform a multiple correspondence analysis (Proc CORRESP; SAS 9.4) (SAS Institute, 2013) in order to explore relationships among these class variables and to select the most interesting variables to be included in the model for GLMselect. The class variables and their definitions are: UdderFill (< 50%, ≥ 50%), MilkingInterval (< 8.5, ≥ 9 h), UdderYield (< 12 kg, ≥ 12 kg) UdderTime (< 4 min, ≥ 4 min), UdderPMF (< 5.6 kg / min, ≥ 5.6 kg / min) UdderAMF (< 3 kg / min, ≥ 3 kg / min, BoxPrepTime (< 2.8 min, ≥ 2.8 min), LastQuarterTime (< 0.9 min, ≥ 0.9 min), MaxQyield (< 3.8 kg, ≥ 3.8 kg), BoxTime (<7 min, ≥ 7 min).

The SAS GLMselect procedure was used to explore associations in the dataset. The procedure is intended to aid in the selection of candidate models. We used the stepwise method in which model 'candidates' are included in a forward stepwise fashion and assessed for their influence on the Schwarz Bayesian information criterion (SBC). If the effect does not improve the model fit (lower SBC) it is rejected and effects already in the model may be removed. If two effects are linearly correlated the procedure will accept only the effect with the lowest SBC. The procedure ends when the SBC criteria is no longer reduced, and the effects are displayed in sorted order from best to worst of the selection criterion. As DIM was an effect of interest with a well-known non-linear relationship with milk production, the dataset was divided into early lactation (< 40 DIM) and late lactation (≥ 40 DIM). Both UdderYield and UdderMPR showed reasonably linear responses within these two periods.

Results and discussion

The results of the multiple correspondence analysis are presented in Figure 1. Three distinct relational groups were identified. Group A showed correspondence between high BoxTime, high UdderTime, low UdderAMF, low UdderPMF, high BoxPrepTime and high LastQuarterTime. Group B showed correspondence between low UdderYield, low MaxQyield, short MilkingInterval, and low UdderFill. Group C showed correspondence between high UdderYield, high UdderFill, long MillkingInterval and high MaxQyield.

It is interesting to note that UdderYield was not grouped with UdderTime. This is likely because of other factors such as milking interval, the uniformity of yield across quarters and quarter and udder milk flow rates. Group C indicated that when MilkingInterval was low, Udderfill and UdderYield were also low. Hogeveen *et al.* (2001) found a very high variation in milking interval in AMS's.

The results of the GLMselect analysis are presented in Table 2. Not surprisingly, the best predictor for milk/box/day was the daily sum of BoxTime, explaining 85% of the variation in milk/box/day. This was followed by BoxAMF, which increased the R-square of the model to 99%. All other effects explained less than 1% of the variation in milk/box/day.

As an example of how to interpret the estimates, each additional minute of BoxTimeSum was associated with an increase in 1.66 kg of milk/box/day. Our data had an average BoxTimeSum of 16.9 hours or 70% of the day, very similar to the 16.8 hours reported by Tremblay *et al.* (2016). A practical maximum for BoxTimeSum is about 22 hours, or 92% of the day, leaving two hours for cleaning and other time that the box is not used for milking. Barn designs including traffic patterns, the number of robots per pen, manure removal strategies and many other details become increasingly important when increasing the number of milkings per day and milk/cow/day in an AMS. Achieving this high level of use would require advances in barn design, a pre-selection strategy and perhaps some form of guided cow traffic. Milking frequency has been identified as a main factor affecting box utilisation (Bach *et al.*, 2009), indicating the interaction between facility design and milking management strategies.

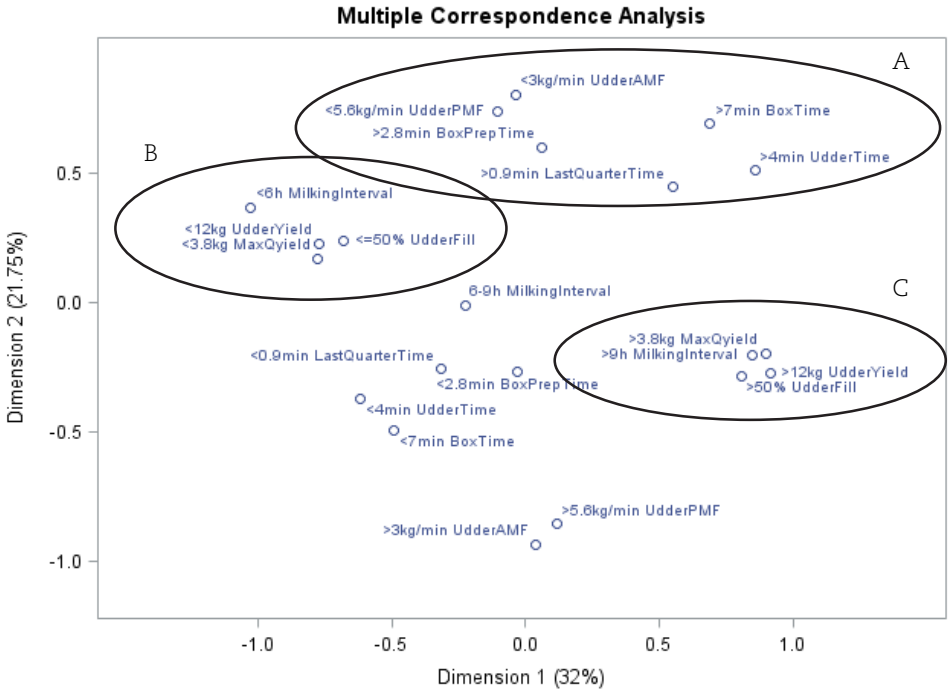

Figure 1. Multiple correspondence analysis

In guided flow systems cows must go through a selection gate or through the AMS box when moving from resting to feeding areas in a barn. With free flow design, cows can move between the AMS, resting and feeding areas without passing through selection gates. Tremblay *et al.* (2016) reported an average of 2.91 milkings per day with 1.89 non-milking visits per day for herds using free cow traffic, assuming that one minute for a non-milking visit would result in an estimate of about 1.6 hours per day of box use for sorting cows. Unal *et al.* (2017) reported that two farms with guided traffic and pre-selection gates had substantially higher maximum capacities (6.5 and 7.2 milkings per hour) than one farm with a free flow barn (4.4 milkings per hour).

Tremblay *et al.* (2016) found that increases in total BoxTime and number of milkings per day were associated with increased milk/box/day. They further investigated the interaction of total BoxTime and milkings per day to arrive at strategies to manage the conflicting goals of maximum production and cost efficiency by selecting cows with high milking speed for pens with greater Cows per Robot.

The second ranked effect associated with milk/box/day was BoxAMF. The GLMselect model for this dependent variable ranked the top three associative effects as UdderAMF, UdderYield and BoxPrepTime. BoxPrepTime averaged 2.85 ± 1.38 minutes and could potentially be reduced to improve BoxAMF. An optimal BoxPrepTime was imagined to be 2.0 minutes, allowing for 1.5 minutes for prep/lag time and an additional 0.5 minutes for cow movement. This assumes improvements in robotic control strategies as have been reported by Brouk (2019). Reduction of udder prep below 1.5 minutes may not produce a reduction in UdderAMF, the effect most associated with BoxAMF, as it would reduce the time available for full udder stimulation and would likely result in an increase in bi-modal milk flow curves.

Table 2. GLMselect results for milk/box/day and for early and late lactation

Model	Effect	R^2	Est.	Effect	R^2	Est.
	All Cows					
Milk/Box/ Day	BoxTimeSum	85%	1.66			
	BoxAMF	99%	287			
	Late Lactation			**Early Lactation**		
BoxAMF	UdderAMF	63%	0.28	UdderAMF	67%	0.31
	UdderYield	81%	0.045	BoxPrepTime	82%	-0.17
	BoxPrepTime	94%	-0.17	UdderYield	94%	0.046
UdderAMF	UdderPMF	78%	0.53	UdderPMF	78%	0.54
	QuarterTimeSTD	85%	-0.56	QuarterDurationSTD	86%	-0.59
	UdderYield	88%	0.009	UdderYield	89%	0.008
UdderPMF	UdderYield	11%	0.12	QuarterPMFSTD	9%	2.62
	QuarterTimeSTD	23%	-1.4	UdderFill	17%	2.46
	QuarterPMFstd	34%	2.5	QuarterDurationSTD	30%	-1.32
UdderYield	MaxQyield	80%	0.95	MaxQyield	81%	0.87
	QuarterYieldSTD	93%	-0.94	QuarterYieldSTD	92%	-0.89
	UdderFill	94%	17	UdderFill	93%	17
UdderMPR	UdderYieldMax	98%	0.37	UdderYieldMax	98%	0.4
	DIM (x100)	19%	-0.081	MilkingInterval	13%	-0.11
	MilkingInterval	29%	-0.086	UdderFill	47%	0.8
UdderFill		58%	1.52	BoxAMF	52%	0.65

UdderAMF was positively associated with UdderPMF (i.e. udders with high peak flow rates also have high average flow rates), negatively associated with intra udder variability of the time to milk individual quarters, QuarterTimeSTD, and positively associated with UdderYield (i.e. fuller udders spend more time in peak flow and a smaller fraction of the milking time in low flow). Precision milking management could be applied to reduce the variability between quarter milk times. The slowest quarter could be milked faster to match the time of the next slowest quarter. This could be achieved by using more aggressive pulsation or by early teatcup removal of the last quarter. Both of these strategies merit investigation to ensure that negative consequences do not result.

One of the fundamental management decisions on a dairy farm is the feeding strategy. Dairy managers choose an optimal MPR based on the cost of feed components and calculus of income over feed costs. One way that box style AMS technology can improve the economic performance of a dairy farm is to implement precision concentrate feeding of individual cows in the milking stall (or separate concentrate feeding stall). Our initial estimates suggest that this advantage is considerable and underutilised in current practice.

Scenarios were created to test the theoretical limits of improving milk/box/day. Milk production per cow has shown a linear increase of about 130 kg/cow/year in the US over the past 50 years as the result of improvements in genetics, reproduction, feeding and

housing. The current US average is about 33 kg/cow/day, with well managed confined herds routinely exceeding a milk production rate of 40 kg/cow/day. We will use production levels of 30 kg/cow/day (1.25 kg/cow/hr), 40 kg/cow/day (1.67 kg/cow/hr) and 50 kg/cow/day (2.08 kg/cow/hr) to represent a range of present and future milk production performance.

A reduction in BoxPrepTime from 2.85–2.0 minutes was modeled with our data set resulting in a predicted increase in BoxAMF from 1.79 kg / min to 1.95 kg / min. The strategy to increase UdderAMF by reducing QuarterTimeSTD resulted in an increase in UdderAMF from 3.08 kg / min to 3.94 kg / min.

Both BoxAMF and UdderAMF are positively associated with UdderYield (per milking). The distribution of UdderYield and UdderFill in our dataset indicated that there was a considerable number of milkings that were performed on cows with low UdderFill. This reduced milk/box/day because time was being used to milk cows that do not require milking as well as the associated reduction in average flow rates for cows with low UdderFill.

The effects of applying a minimum expected milk yield were investigated with our data set. Applying a minimum expected yield must be applied with caution. Increasing milking frequency (reduced MilkingInterval) is a well-known way to increase MPR in early lactation. We modeled a milking permission strategy that required all cows in early lactation be milked every six hours (four times per day) and applied a minimum expected milk yield of 12 kg (the average for our study herd) and 15 kg (upper quartile of our study herd) for milking permission of later lactation cows (> 50 DIM). The results of these UdderYield milking permissions combined with the reduced BoxPrepTime and QuarterTimeSTD strategies and with 22 hours per day of box occupancy for milking are presented in Table 3.

Table 3. Results of theoretical milking scenarios in automatic milking systems

Cow MPR (kg/hr)	Cow MPR (kg/day)	12 kg milking permission limit		15 kg milking permission limit	
		Milking frequency	Cows/ box	Milking frequency	Cows/ box
1.25	30	2.5 / day	119	2.0 / day	127
1.67	40	3.3 / day	89	2.7 / day	95
2.08	50	4.2 / day	71	3.3 / day	76

Limiting the data set to observations with greater than 12 kg or 15 kg per milking results in an UdderAMF of 4.25 and 4.36 kg / min, BoxAMF of 2.70 kg / min or 2.89 kg / min, respectively. The predicted milk harvest was 3,570 kg/box/day kg for the 12 kg milking permission limit and 3,810 kg/box/day for the 15 kg milking permission limit. This is more than double current practice (1,630 kg/box/day) as reported by Tremblay *et al.* (2016).

Reinemann (2002) postulated that a doubling of the productivity/cost ratio for box-style AMS technology would make it economically competitive with other methods of milk harvesting. The reassessment of productivity of AMS technology 15 years later indicates that progress has been made and further advances in productivity/cost ratio are within the realm of possibility.

At the highest MPR, the number of cows per box is comparable to that predicted by De Koning & Rodenburg (2004) who estimated in the early days of AMS that one box was sufficient for 60 – 70 cows. The theoretical upper limit to the number of cows per box for the mid and lower level MPR are considerably higher than this early projection and far

above current practice of 50.5 cows/box as reported by Tremblay *et al.* (2016). Achieving the very high stocking density for the 30 kg/day and 40 kg/day MPR scenarios would require considerable advancement in barn design and cow traffic management as noted above.

An insight from this study which may aid in the process of increasing the number of cows per pen is to set milking permission MilkYield limits progressively higher as cows are added, to allow for the increased number of milkings required for the added cows. Such a strategy could be used to explore the optimal number of cows per pen and per AMS box in existing systems. One reason that AMS managers give for allowing 'free time' is to accommodate interruptions in milking due to maintenance or breakdown. This is a high continuous price to pay for what is hopefully becoming a rarer occurrence. Another strategy to manage this risk is a 'recovery' mode in which milking permissions are adjusted after AMS inactivity to milk the cows most in need due to extended milking interval and high UdderFill.

Conclusions

Several prospects for precision milking management to improve the capital efficiency of box-style AMS technologies were identified in this study. The largest area of potential improvement appears to be using milking management strategies to increase the percentage of time that each AMS box is actually milking cows. This could be achieved by a combination of milking permission udder fill limits, increased number of cows per AMS, with improved barn design and cow traffic strategies required to realise this potential. There is also potential to reduce within udder variability of quarter milking times by milking slow quarters faster while further gains could be realised by reducing udder preparation and teatcup attachment time through advances in robotic control.

Integration of economic models with milking performance data also offers opportunities for increased efficiency by using precision feeding to optimise income over feed cost, identification of cows for breeding, culling and dry off and developing optimal milking management strategies. A fundamental value-added proposition of precision milking management is to test and report on the effects of feeding, milking permission, milking machine settings and other milking management strategies on MPR and profitability. In this way, every day is a new experiment and part of a continuous improvement process.

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References

Bach, A., M. Devant, C. Iglesias and A. Ferrer (2009). Forced traffic in automatic milking systems effectively reduces the need to get cows, but alters eating behaviour and does not improve milk yield of dairy cattle. *Journal of D*airy Science, 92: 1272–1280.

Brouk, M. Economics of Robotic Milking (2019). Western Dairy Management Conference 2019.

De Koning, K., and J. Rodenburg. (2004). Automatic milking: State of the art in Europe and North America. In A better understanding of automatic milking, ed. A. Meijerling, H. Hogeveen, and C.J.A.M. De Koning, 27–37. Wageningen: Wageningen Academic Publishers.

Hamann, J. (2002). Machinemilking effects on udder health – comparison of a conventional with a robotic milking system. The First North American Conference on Robotic Milking.

Hogeveen, H., W. Ouweltjes, C. de Koning, and K. Stelwagen. (2001). Milking interval, milk production and milk flow-rate in an automatic milking system. *Livest. Prod. Sci*., 72(1-2): 157–167.

Penry, JF, PM Crump, LL Hernandez, and DJ Reinemann. (2018). Association of quarter milking measurements and cow-level factors in an automatic milking system. *Journal of D*airy Science, 101(8): 7551–7562.

Reinemann, D.J, P.L. Ruegg, and M.A. Davis (2001). Assessment of robotic milking in Wisconsin. Written for presentation at the 2001 ASAE Annual International Meeting.

Reinemann, D.J. (2002). Evolution of Automated Milking In the USA. Proc First North American Conference on Robotic Milking, March 20-21, 2002, Toronto, Ontario, Canada.

SAS Institute (2013). SAS 9.4. SAS Institute, Cary, NC.

Schewe, R.L. and Diana Stuart (2014). Diversity in agricultural technology adoption: How are automatic milking systems used and to what end? *Agric Hum Values,* 32: 199–213.

Stuart, D., R.L. Schewe, and R. Gunderson. (2013). Extending social theory to farm animals: Addressing alienation in the dairy sector. *Sociologia Ruralis*, 53(2): 201–222.

Tremblay, M., Justin P. Hess, Brock M. Christenson, Kolby K. McIntyre, Ben Smink, Arjen J. van der Kamp, Lisanne G. de Jong, Dörte Döpfer (2016). Factors associated with increased milk production for automatic milking systems. *Journal of* Dairy Science, 99: 3824–3837.

Unal, H., Kuraloglu, H., Koyuncu, M., Alibas, K. (2017). Effect of cow traffic type on automatic milking system performance in dairy farms. *The Journal of Animal & Plant Sciences*, 27(5): 1454–1463.

Effect of changing teatcup removal and vacuum settings on milking efficiency of an automatic milking system

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Abstract

The aim of this experiment was to assess strategies to reduce milking time in a pasture based automatic milking system (AMS). Milking time is an important factor in automatic milking because it represents the largest portion of box time and any reductions in box time can facilitate more milkings per day and hence higher production levels per milking robot. This study evaluated two removal milk flow switch points; 30% and 50% of average flow-rate at the quarter-level, a strategy to increase system vacuum during the peak milk flow period, and the interaction of these effects on milking time in an AMS. No significant differences in the milking efficiency parameters of milk flow-rate, milk yield, box time, milk time and milking interval were found between treatments in this study on cows milked in an AMS on a pasture based system, where average and peak milk flows of 2.15 kg / min and 3.48 kg / min respectively were observed during the experiment. Small increases in maximum milk flow-rate were detected (0.09 kg / min) due to the effect of increasing the system vacuum during the peak milk flow period. These small increases in maximum milk flow-rate were not sufficient to deliver a significant reduction in milk time or box time. Furthermore, increasing the removal setting from 30% of average flow to 50% of average flow was not an effective means of reducing box time. This was because the resultant increase in removal flow-rate of 0.12 kg / min was not enough to deliver practical or statistically significant decreases in milk time or box time.

Key words: Milking, removal settings, milking vacuum

Introduction

The cluster-on times of individual cows is an important factor for determining herd milking times and thus, labour efficiency in conventional milking systems. In the context of automatic milking systems (AMS), cluster on-time has a direct impact on cow box time and hence, the number of milkings that are possible per day. It has been reported that the cluster-on time of cows can be reduced, without affecting milk yield or udder health indicators, by increasing the automatic cluster remover (ACR) milk flow switch point at the udder-level (Burke & Jago, 2011, Jago *et al.*, 2010, Magliaro & Kensinger, 2005, Rasmussen, 1993, Stewart *et al.*, 2002). A study by Edwards *et al.* (2013a) which was carried out on dairy cows in late lactation reported that udder-level ACR milk flow switch points up to 0.8 kg / min reduced individual cluster-on times without affecting milk yield or indicators of udder health when using a milking routine with no pre-milking stimulation, as is common practice on pasture-based dairy farms (Edwards *et al.*, 2013a). Increasing ACR milk flow switch point had no effect on indicators of udder health despite greater residual milk due to earlier removal of the cluster (Burke & Jago, 2011, Edwards *et al.*, 2013a). Increasing evidence indicates that an increase in residual milk does not adversely affect SCC or rates of clinical mastitis (Burke & Jago, 2011, Clarke *et al.*, 2008, Edwards *et al.*, 2013b, Jago *et al.*, 2010). However, Burke & Jago (2011) noted a 1% reduction in milk production (kg / day) as a result of applying 0.4 kg / min udder-level milk flow switch point compared with 0.2 kg / min. In addition, Magliaro & Kensinger (2005) documented a 2.5% reduction in milk yield (kg / milking) for the 0.8 kg / min udder-level milk flow switch point when compared to the 0.48 kg / min setting.

Many automatic milking systems have the ability to carry out teatcup removal at the quarter-level. To address this topic Krawczel *et al.* (2017) carried out an experiment with teatcup removal milk flow switch points ranging from 0.06–0.48 kg/min at the quarter-level. The effect of changing teatcup removal milk flow switch point setting was significant with the highest setting resulting in the lowest milking time. Milk yield, peak flow or average flow were not affected by milk flow switch point level (Krawczel *et al.*, 2017). The milking interval was maintained at eight hours in the studies of Ferneborg *et al.* (2016) and Krawczel *et al.* (2017). However, in seasonal pasture based AMS farms, the milking interval is generally between 12–18 hours depending on the stage of lactation and level of concentrate feed allocation (Shortall *et al.*, 2018). Furthermore, not every AMS teatcup removal system works on the basis of specifying a milk flow switch point flow-rate. Hence, further research is required to investigate the effects of applying different teatcup removal strategies (e.g. % of average flow-rate) on the milking time of cows.

In addition to offering the user adjustable removal settings, many AMS offer an option to adjust the system vacuum level, or apply a vacuum level that depends on the milk flow-rate. It is widely accepted that increasing vacuum levels increases the peak milk flow-rate and milking speed (Rasmussen & Madsen, 2000, Spencer *et al.*, 2007). There is a gap in knowledge in the literature around the effects of varying the vacuum during the peak milk flow period on milking time and also on how these settings would affect the milking time across different removal settings in an AMS.

The aim of this experiment, therefore, was to measure the effect of adjusting the teatcup removal milk flow switch point (as a percentage of average quarter-level flow-rate) on the milking time of cows as well as the effect of varying the milking system vacuum during the peak milk flow period on the effect of different removal settings in a pasture based AMS.

Materials and methods

This experiment was carried out at the research facility at Teagasc Moorepark, Cork, Ireland. The research farm operated a spring calving, grass based system. Cows were milked using a single Astronaut A4robotic milking system (Lely, The Netherlands). The AMS was equipped with the custom take-off (CTO) module that enabled adjustment of the teatcup removal milk flow switch point as well as the time-delay of the teatcup removers from trigger flow level to removal of the teatcup from the teat. The AMS system vacuum level was set to 43 kPA and the pulsation system operated on a pulsator ratio of 65:35 with 60 pulses per minute.

Experimental treatments

The treatments consisted of two teatcup milk flow switch point settings and two vacuum settings. Normal removal (NR) removed the teatcup from the teat when the instantaneous milk flow-rate dropped below 30% of the average milk flow-rate for that teat, early removal (ER) removed the teatcup when the instantaneous milk flow-rate dropped below 50% of the average flow-rate for that teat; Normal vacuum (NV) maintained the default system vacuum of 43 kPA for the entire milking, dynamic vacuum (DV) increased the system vacuum level (from the default of 43 kPA) by 1 kPa for each kg / min of milk flow over 2 kg/min. Hence, the four treatments were described as 1) normal removal with normal vacuum (NRNV); 2) early removal with normal vacuum (ERNV); 3) normal removal with dynamic vacuum (NRDV) and 4) early removal with dynamic vacuum (ERDV). The time delay from the quarter flow-rate reaching the milk flow switch point and removal of the teatcup was set to three seconds.

Cows were split into four groups and transitioned through the four treatments in a 2 × 2 factorial design. The treatments were applied in four experimental periods of three days

each with a two day washout period (where the cows were milked with NRNV) between the experimental periods. The washout days were put in place to eliminate carry over effects between treatment periods. The NRNV treatment was used to milk the cows during the week before the experiment start date.

Cow selection

Cows were suitable for enrolment in the study provided they did not present with a clinical case of mastitis during the 2017 milking season and had an udder-level SCC less than 200,000 cells / ml at a milk recoding test carried out three days before implementation of the first experimental treatment period. Milk samples were collected using the Shuttle (Lely, The Netherlands) and SCC was measured using a Fossomatic machine (Foss, Denmark). Milk samples were treated in the Shuttle using Broad spectrum microtabs (Advanced Instruments Inc. MA, USA) in each milk sampling bottle to preserve the sample until it was transported to the milk testing laboratory.

A group of 77 cows were enrolled in the experiment which contained 68 Holstein Friesians, seven Jerseys and two Norwegian reds. Cows were 179 DIM (range 110 – 234 DIM) and ranged in parity from one to seven (average 3). Average milking interval was 14.2 hours (range 7.3–24.5 hours). Milk production per milking was 9.6 L (range 2.2 – 24.8 L). Cows were blocked and randomly assigned to four experimental groups by breed (FR, JE, NR), Parity (1, >1) and maximum milk flow-rate (< 3.5, > = 3.5 kg/min).

Data management and statistical analysis

Data reports were combined from the AMS and the milk testing laboratory using spread sheets. Data were manipulated and filtered in SAS 9.4 (SAS Institute Inc, NC, USA). The following pre-processing steps were carried out: box times greater than 15 minutes were removed, milk yields of less than 1.5 kg per milking were removed. These steps removed 4% of raw data points. The following mixed model procedure (Proc GLMIX, SAS 9.4 Statements: Reference, Fourth Edition, SAS Institute Inc, NC, USA) was used to assess if the dependent variable (y in equation 1) was influenced by the treatments.

$$y = Treatment + Block \quad [1]$$

Where y = milk time (s) i.e. duration of milk flow, or box time (s) i.e. period that the cow was present in the AMS, or average milk flow-rate (kg/min), or maximum milk flow-rate (kg/min). Treatment (NRNV, NREV, ERNV, ERDV), block (1–8) and CowID were chosen as class variables. CowID was declared as a random variable and a repeated measure with an auto regressive covariance structure, AR(1).

A similar model structure was used to determine the effect of vacuum and removal settings independently. The following mixed model procedure (Proc GLMIX, SAS 9.4 Statements: Reference, Fourth Edition, SAS Institute Inc, NC, USA) was used to assess if the dependent variable (y in equation 2) was influenced by the treatments.

$$y = Removal + Vacuum + Removal * Vacuum + Block \quad [2]$$

Where y = milk time (S), or box time (S), or average milk flow-rate (kg/min), or maximum milk flow-rate (kg/min). Removal (NR or ER), Vacuum (NV or DV), block (1–8) and CowID were chosen as class variables. CowID was declared as a random variable and a repeated measure with an auto regressive covariance structure, AR(1).

Results and discussion

Effect of treatment

Table 1 shows the LS means for six key milking efficiency parameters for each treatment, which were generated using the model described in equation 1. The main effect of treatment on average milk flow-rate, milk yield, box time, milk time and milking interval was not significant. P values are displayed in Table 1. The effect of treatment on maximum milk flow was significant ($P = 0.04$). Treatment NRDV had a maximum milk flow of 3.33 kg / min which was 5% larger than the smallest maximum milk flow of treatment ERNV.

Table 1. Effect of treatment on six key milking efficiency parameters. P values displayed indicate the significance of treatment on each parameter. Parameters with different letter groups within rows differ significantly at the $P < 0.05$ level

Parameter	Treatments								P values
	NRNV[2]	SEM[1]	NRDV[3]	SEM[1]	ERNV[4]	SEM[1]	ERDV[5]	SEM[1]	Treatment
Average milk flow (kg/min)	2.04[a]	0.07	2.04[a]	0.07	2.00[a]	0.07	2.06[a]	0.07	0.38
Max milk flow (kg/min)	3.25[ab]	0.10	3.33[a]	0.10	3.18[b]	0.10	3.28[ab]	0.10	0.04
Milk yield (kg)	9.58[a]	0.31	9.56[a]	0.31	9.39[a]	0.31	9.72[a]	0.31	0.56
Box time (s)	390[a]	13	391[a]	13	390[a]	13	391[a]	13	0.10
Milk time (s)	316[a]	13	315[a]	13	313[a]	13	317[a]	13	0.90
Milking interval (hr)	14.28[a]	0.30	14.38[a]	0.30	13.91[a]	0.30	14.25[a]	0.30	0.47

[1] SEM = Standard error of the mean [2] NRNV - normal removal with normal vacuum [3] NRDV - normal removal with dynamic vacuum: [4] ERNV - early removal with normal vacuum: [5] ERDV - early removal with dynamic vacuum

Effect of removal and vacuum

Table 2 shows the LS means for six key milking efficiency parameters for each level of removal setting (normal and early) and for each level of vacuum setting (normal and dynamic). These LS means were generated using the model described in equation 2. The interactive effect of removal*vacuum was not significant ($P > 0.8$) for any of the dependent variables and was removed from the final model. The effect of removal setting on average milk flow-rate, maximum milk flow-rate, milk yield, box time, milk time and milking interval was not significant. P values are displayed in Table 2.

The effect of vacuum setting on average milk flow-rate, milk yield, box time, milk time and milking interval was not significant. P values are displayed in Table 2. The effect of vacuum setting on maximum milk flow was significant ($P = 0.01$). The dynamic vacuum setting had a maximum milk flow of 3.30 kg / min which was 2.5% larger than the maximum milk flow-rate of the normal vacuum setting.

Table 2. Effect of removal milk flow switch point setting and vacuum setting on 6 key milking efficiency parameters. P values displayed indicate the significance of removal setting or vacuum setting on each parameter

	Removal					Vacuum				
Treatment	**Normal**	**SEM[1]**	**Early**	**SEM[1]**	**P Value**	**Normal**	**SEM[1]**	**Dynamic**	**SEM[1]**	**P Value**
Average milk flow (kg/min)	2.04	0.07	2.03	0.07	0.78	2.02	0.07	2.05	0.07	0.17
Max milk flow (kg/min)	3.29	0.09	3.23	0.09	0.20	3.22	0.09	3.30	0.09	0.01
Milk yield (kg)	9.57	0.29	9.56	0.29	0.92	9.49	0.29	9.64	0.29	0.31
Box time (s)	391	13	391	13	0.93	390	13	391	13	0.85
Milk time (s)	316	13	315	13	0.91	315	13	316	13	0.72
Milking interval (hr)	14.33	0.25	14.08	0.25	0.31	14.09	0.24	14.31	0.24	0.27

[1] SEM = Standard error of the mean

An increase in system vacuum was applied at 93% of milkings that were assigned to the dynamic vacuum setting; i.e. 93% of milkings exceeded a maximum milk flow-rate of 2 kg / min and hence experienced a system level vacuum increase of at least 1 kPa. An increase of 2 kPa in system vacuum was applied to 64% of milkings, a 3 kPa increase was applied at 34% of milking, a 4 kPa increase was applied at 12% of milkings and a 5 kPa increase was applied at 1% of milkings.

The extent to which the dynamic vacuum treatment influenced milk time in this study would have depended on the length of time that the flow-rate remained above the milk flow switch point of 2 kg / min, and hence the length of time during each milking that the dynamic vacuum setting was being applied. Hence, for herds with longer and higher peak milk flows, a larger effect due to the DV setting may be expected. In order to understand how this dynamic vacuum setting functioned in more detail in this study, flow profile data would be required at each milking. However, this information was not available from the AMS used in this study.

No significant differences in the milking efficiency parameters of milk flow-rate, milk yield, box time, milk time and milking interval were found between the normal and early removal settings in this study. This was likely due to the relatively low average udder-level and quarter-level flow-rates observed. The average flow-rate of all milkings on the early removal setting was just 0.01 kg / min higher than the normal removal setting. This is likely because the average quarter-level removal flow-rate was just 0.12 kg / min higher on the early removal setting (0.37 kg / min) versus the normal removal setting (0.22 kg / min). This increase was likely insufficient to bring about a practical or statistically significant change in milk time or box time.

The average interval between milkings in this study was 14.2 hours (1.7 milkings per day) which differs from other studies where cows were milked much more frequently, from 6.7–7.8 hours in the study of Krawczel *et al.* (2017). Hence, results from teatcup removal

studies with milking intervals of greater than twice per day should be interpreted with caution in the context of pasture based AMS farms where milking intervals tend to drop below twice per day.

Conclusion

No significant differences in the milking efficiency parameters of milk flow-rate, milk yield, box time, milk time and milking interval were found between treatments in this study on cows milked in an AMS on a pasture based system. Small increases in maximum milk flow-rate were detected (0.09 kg / min) due to the effect of increasing the vacuum when the milk flow-rate increased beyond the udder-level milk flow switch point of 2 kg / min. These small increases in maximum milk flow-rate were not sufficient to deliver a significant reduction in milk time or box time. Furthermore, increasing the removal setting from 30% of average flow to 50% of average flow was not an effective means of reducing box time. This is because the resultant increase in removal flow-rate of 0.12 kg / min was not enough to deliver practical or statistically significant decreases in milk time or box time.

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References

Burke, J.K. & J.G. Jago. (2011). Comparing somatic cell counts, production and milking durations of dairy cows when milked at two automatic cup-removal flow-rate thresholds. *Animal Production Science*, 51(10): 920–924.

Clarke, T., E.M. Cuthbertson, R.K. Greenall, M.C. Hannah, and D. Shoesmith. (2008). Incomplete milking has no detectable effect on somatic cell count but increased cell count appears to increase strip yield. *Australian Journal of Experimental Agriculture*, 48(9): 1161–1167.

Edwards, J.P., J.G. Jago, and N. Lopez-Villalobos. (2013a). Milking efficiency for grazing dairy cows can be improved by increasing automatic cluster remover thresholds without applying premilking stimulation. *J Dairy Sci*, 96(6): 3766–3773.

Edwards, J.P., J.G. Jago, and N. Lopez-Villalobos. (2013b). Short-term application of prestimulation and increased automatic cluster remover threshold affect milking characteristics of grazing dairy cows in late lactation. *J Dairy Sci*, 96(3): 1886–1893.

Ferneborg, S., L. Stadtmüller, J. Pickova, L. Wiking, and K. Svennersten-Sjaunja. (2016). Effects of automatic cluster removal and feeding during milking on milking efficiency, milk yield and milk fat quality. *Journal of Dairy Research*, 83(2): 180–187. doi:10.1017/S0022029916000170.

Jago, J.G., J.L. Burke, and J.H. Williamson. (2010). Effect of automatic cluster remover settings on production, udder health, and milking duration. *Journal of Dairy Science*, 93(6): 2541–2549.

Krawczel, P., S. Ferneborg, L. Wiking, T.K. Dalsgaard, S. Gregersen, R. Black, T. Larsen, S. Agenäs, K. Svennersten-Sjaunja, and E. Ternman. (2017). Milking time and risk of over-milking can be decreased with early teat cup removal based on udder quarter milk flow without loss in milk yield. *Journal of Dairy Science*, 100(8): 6640–6647.

Magliaro, A.L. & R.S. Kensinger. (2005). Automatic Cluster Remover Setting Affects Milk Yield and Machine-On Time in Dairy Cows. *Journal of Dairy Science*, 88(1): 148–153.

Rasmussen, M.D. (1993). Influence of switch level of automatic cluster removers on milking performance and udder health. *Journal of Dairy Research*, 60(3): 287–297.

Rasmussen, M.D. & N.P. Madsen. (2000). Effects of Milkline Vacuum, Pulsator Airline Vacuum, and Cluster Weight on Milk Yield, Teat Condition, and Udder Health. *Journal of Dairy Science*, 83(1): 77–84.

Shortall, J., C. Foley, R.D. Sleator, and B. O'Brien. (2018). The effect of concentrate supplementation on milk production and cow traffic in early and late lactation in a pasture-based automatic milking system. *Animal*, 12**:** 853–863.

Spencer, S.B., J.W. Shin, G.W. Rogers, and J.B. Cooper. (2007). Short Communication: Effect of Vacuum and Ratio on the Performance of a Monoblock Silicone Milking Liner. *Journal of Dairy Science*, 90(4): 1725–1728.

Stewart, S., S. Godden, P. Rapnicki, D. Reid, A. Johnson, and S. Eicker. (2002). Effects of Automatic Cluster Remover Settings on Average Milking Duration, Milk Flow, and Milk Yield. *Journal of Dairy Science* 85(4):818–823.

Effect of teatcup removal setting on milking efficiency and udder health in a pasture based AMS

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Abstract

Milking duration is an important factor in automatic milking systems (AMS) because it can affect the quantity of milk harvested by the AMS during the day and hence influence farm profitability. One strategy to achieve shorter milking times is to increase the milk flow switch point, i.e. the milk flow-rate at which the teatcup is removed. The aim of this study was to measure the effect of three teatcup removal strategies on box time (time in the AMS), milking duration, milk production rate and somatic cell count in a pasture based AMS.

The three teatcup removal strategies tested in this study consisted of removing the teatcups when the quarter milk flow-rate fell below 20% of the quarter's rolling average milk flow-rate (MFR20), 30% of the quarter's rolling average milk flow-rate (MFR30) and 50% of the quarter's rolling average milk flow-rate (MFR50).

The milk time (duration of the cow's milking) of MFR30 was nine seconds shorter than MFR20. The milk time of MFR50 was eight seconds shorter than MFR20. These results were statistically significant. No differences were found between MFR30 and MFR50. Additionally, there was no difference in milk production rate or somatic cell count between any of the treatments. The shorter box time for the MFR30 and MFR50 strategies could allow for at least three extra milkings per day.

Key words: Teatcup removal, automatic milking, milking efficiency, somatic cell count

Introduction

In automatic milking systems (AMS), it is important to maximise efficiency by increasing milking capacity to have an earlier return on investment. Milking capacity can be defined as the number of milkings performed by the robot in a day (Castro *et al.*, 2012). In order to achieve an increased number of milkings in the AMS, two of the main strategies are to manage cow incentives to provide a steady stream of cows presenting themselves to be milked (such that the robot free time is reduced) and to reduce the time it takes for each milking to be performed. In a study conducted by Castro *et al.* (2012), the most important factors determining the milk yield per robot per year were the average milk flow-rate during a single milking and the number of cows milked per robot per day. Therefore, increasing milking speed could allow for the robot to milk more cows and this has the potential to increase the amount of milk that is harvested per robot each year (Castro *et al.*, 2012).

In conventional milking systems, a strategy to reduce milking time that has been studied is to increase the milk flow switch point in the cluster (milk flow-rate at which the cluster is removed). However, there is a common farmer concern that this strategy could have a negative impact on milk production or udder health. Edwards *et al.* (2013) showed that increasing the cluster removal switch point from 0.2 kg / min to 0.8 kg / min at the udder level, reduced milking time by 18–26% without affecting somatic cell count (SCC) or milk

production variables. Additionally, Burke & Jago (2011) found that milking duration was reduced by 11% by changing the cluster removal setting from 0.2 kg / min to 0.4 kg / min at the udder level without negatively affecting somatic cell count, but with a slight drop in milk production (1%). In automatic milking systems, Krawczel *et al.* (2017) found a reduction in milking time of 0.9 minutes when they increased the teatcup removal level from 0.06 kg / min to 0.48 kg / min at the quarter level without any negative effects on milk yield or somatic cell count, however, the milking interval was maintained at around eight hours which is not a usual scenario in pasture based automatic milking systems. Milking intervals tend be greater and more variable with pasture based AMS than conventional milking and indoor AMS (Davis *et al.,* 2005), thus, variation in the degree of udder filling milking time is observed. The degree of udder filling has been shown to affect the start of milk ejection (Bruckmaier & Hilger, 2001) and potentially milking time. Therefore, evaluation of the effect of teatcup removal settings on milking time in pasture based AMS could provide new knowledge to milking management research. Additionally, there have not been studies conducted on evaluating the impact of a removal strategy that uses a percentage of the average milk flow-rate on milking duration.

The objective of this study was to quantify the effects of three percentage based teatcup removal strategies on box time (time in the AMS), milking time, milk production rate, and somatic cell count.

Materials and methods

This experiment was conducted at the research facility at Teagasc, Ireland. The herd consisted of 86 spring calving cows being milked in a single Astronaut A4 robotic milking system (Lely, The Netherlands). The system vacuum level was set to 43 kPa, pulsation ratio of 65:35, and pulsation rate of 60 per minute.

The treatments consisted of three percentage based teatcup removal settings. One of them removed the teatcup when the quarter flow-rate fell below 20% of the quarter's rolling average milk flow-rate (MFR20). The second treatment removed teatcups when quarter milk flow-rate dropped below 30% of the rolling average milk flow-rate (MFR30) and a third teatcup removal strategy was used when quarter milk flow-rate dropped below 50% of the rolling average milk flow-rate (MFR50). There was a teatcup removal flow-rate limit of 0.5 kg / min, which prevented teatcups to be removed if the quarter milk flow-rate was above this limit. The teatcup removal setting is implemented at the cow level but the decision for teatcup removal is made at the quarter level, therefore, the experimental unit was the cow.

Seventy-five cows were selected for this trial on the basis of no previous clinical mastitis case during the current lactation and an udder level SCC of less than 200,000 cells/ml at a milk test conducted a week prior to the start of the experiment. Cows were blocked based on parity, breed and maximum milk flow-rate and cows in each block were randomly assigned to one of three groups.

The experimental design was a crossover design where each group was assigned one of the three teatcup removal treatments during one week and then groups were switched to a different treatment until they had transitioned through all of the treatments over a period of three weeks. Milk samples were collected at the end of each treatment week using the Shuttle (Lely, The Netherlands) and SCC was measured using a Fossomatic machine (Foss, Denmark).

Milking data obtained from the AMS farm management software (Lely T4C) were combined with the milk testing laboratory SCC results. Milk sampling causes an increase in box time

and therefore only the first five days of each treatment period were used for the analysis of milking performance outcome variables. Cow milk production rate (kg/hr) was calculated by dividing milk production for each milking by the milking interval. Somatic cell counts were Log10 transformed due to the skewed nature of the data. Two cows developed clinical mastitis during the experiment and were removed from the dataset for final analysis. Both cows were from Group 3, one case occurred during the MFR 50 treatment and the second while on the MFR20 treatment.

The outcome variables analysed were Box Time (BT), Milk Time (MT), Milk Production Rate (MPR) and Somatic Cell Score (SCS, log10 of somatic cell count). The mixed procedure (Proc Mixed, SAS 9.4 Statements: Reference, Fourth Edition, SAS Institute Inc, NC, USA) was used. Week (1, 2, 3), Treatment (MFR20, MFR30, MFR50), Block (1–8), Group (1, 2, 3) and Cow were declared as class variables. Week, Treatment, Lactation and Milk Yield were classified as fixed effects. Cow (Group) was declared as a random variable. To account for auto-correlation of repeated measures on the same experimental unit (cow), we used an AR(1) error structure.

Results and discussion

Descriptive data for the study herd is shown in Table 1. Cows were on average on their third lactation, were 82 days in milk at the start of the experiment, produced 19 kg of milk per day and were milked every 14 hours.

Table 1. Summary of several herd and milking parameters during the experimental period

Parameter	Mean	STD[1]
Lactation	3.3	1.6
DIM start*	82	27
Milk yield/milking (kg)	13.3	4.2
Milk yield/day (kg)	19.3	8
Box time (s)	419	137
Milk time (s)	343	136
Milking interval+ (h)	14.1	4.3

* DIM = Days in Milk at the start the trial period; [1] STD = Standard Deviation

Table 2 shows the effect of teatcup removal settings on the studied parameters. There was evidence that the treatments had an impact on milking time ($P = 0.02$). Milking time for the MFR30 treatment was nine seconds shorter than for the MFR20 treatment ($P < 0.01$) and MFR50 had eight seconds shorter milkings than MFR20 ($P = 0.02$). No differences were found between the MFR30 and MFR50 teatcup removal treatments.

Teatcup removal setting also had an impact on box time (Table 2). Cows that were in the MFR20 teatcup removal setting had 11 seconds ($P < 0.01$) and nine seconds ($P = 0.02$) longer box time than the cows in the MFR30 and MFR50, respectively. Again, no differences were found between the MFR30 and MFR50 removal settings. Milk yield and week had a strong influence on both milking time and box time ($P < 0.001$).

Milk production rate and somatic cell score were not affected by the teatcup removal setting ($P = 0.2$ and $P = 0.34$, respectively). Somatic cell score was affected by milk yield ($P < 0.001$), lactation ($P = 0.01$) and week ($P < 0.001$).

Table 2. Effect of teatcup removal setting on several parameters related to milking efficiency and somatic cell count

Parameter	Treatments						
	MFR20[1]	SEM	MFR30[2]	SEM	MFR50[3]	SEM[4]	P-value
Box time (s)	429[a]	36.8	418[b]	36.8	420[b]	36.8	0.01
Milk time (s)	350[a]	36.8	341[b]	36.8	342[b]	36.8	0.02
MPR* (kg/hr)	0.84	0.1	0.84	0.1	0.83	0.1	0.2
Log^{10} SCC**	4.55	0.05	4.5	0.05	4.51	0.05	0.33

*MPR = Milk production rate; ** Log^{10} SCC = log^{10} transformation of somatic cell count; [1]MFR20 = Teatcup removal at 20% of the average flow-rate; [2]MFR30 = Teatcup removal at 30% of the average flow-rate; [3]MFR50 = Teatcup removal at 50% of the average flow-rate; [4]SEM = Standard Error of the Mean, Different letters indicate significant differences at the $\alpha = 0.05$ level.

This study showed that it is possible to reduce the duration of the milking and the time the cows spend in the box by using a MFR30 and MFR50 teatcup removal settings compared to a MFR20 setting.

We found that milking time was nine seconds longer by taking off the teatcups with the MFR30 setting compared to MFR20, which represented a 2.6% reduction in milking time. These results are in agreement with previous research (Burke & Jago, 2011, Edwards *et al.*, 2013a, Krawczel *et al.*, 2017) where increasing the milk flow-rate for milking unit removal, decreases milking time. However, Burke & Jago (2011) showed that an increase in the cluster milk flow switch point from 0.2 kg / min to 0.4 kg / min resulted in 47 seconds shorter milking times per cow, which represented an 11% reduction, whereas Edwards *et al.* (2013) showed a difference of 40 seconds in cluster on time when cluster milk flow switch point was increased from 0.2 kg / min to 0.4 kg / min (9% reduction). In automatic milking systems Krawczel *et al.* (2017) found that by increasing the quarter teatcup milk flow switch point from 0.06 kg / min to 0.3 kg / min, milking time was reduced by 24 seconds (5.3% reduction).

The present study tested a percentage of the milk flow-rate average as a criterion for teatcup removal, which is different to an absolute milk flow-rate setting. A percentage-based strategy could create more variability in the milk flow-rate at teatcup removal because it is relative to the milk flow-rate of each cow and therefore, a cow with a high average milk flow-rate might have a higher absolute milk flow-rate at teatcup removal than a cow with low milk flow-rates. This AMS does not provide information on the milk flow-rate curves or signals the absolute milk flow-rate at teatcup removal. However, these were estimated by multiplying the teatcup removal setting by the average milk flow-rate (average flow-rate 0.2 × 0.3 or 0.5). Our estimated average milk flow-rate at teatcup removal for MFR20 was 0.16 kg / min and for MFR30 was 0.25 kg / min milk flow-rate, which represents a lower difference in milk flow-rates at teatcup removal than in previous studies. This, added to a larger variation of the milk flow-rate at teatcup removal, could explain the lower milking time difference between these treatments compared to the Krawczel *et al.* (2017) study.

MFR50 had on average eight seconds shorter milking time than MFR20 (2.3% reduction in milking time). These results are in agreement but to a lower degree than what was found by Krawczel *et al.* (2017) where a decrease in milking time from 7.6–6.7 minutes was seen by switching from a 0.06 kg / min removal setting to a 0.48 kg / min, which represented a 12% decrease. No differences in milking times were found between the MFR50 and

MFR30 removal strategies. The AMS used in our study applied a 0.5 kg / min limit, which prevented removal of a teatcup if the calculated removal milk flow-rate was above this level. When the calculated milk flow-rate for teatcup removal was above 0.5 kg / min it resulted in a recalculation of the milk flow switch point which possibly led to a lower milk flow switch point than the one originally calculated which could explaine the lack of differences between the MFR30 and MFR 50 treatments.

Since the milking robot is constantly milking and considering it performs about 140 milkings per day on average, by saving nine seconds per milking it is possible to save 21 minutes a day which, by the average of 5.7 minutes per milking per cow, would allow over 3 more milkings a day or at least one more cow in the robot.

There was not a significant effect of the teatcup removal treatment on the SCS or the milk production rate of the cows in this study, which was in agreement with Edwards *et al.* (2013) in a conventional milking system. Contrary to what many farmers might think, evidence suggests that higher residual milk does not adversely affect SCC (Edwards *et al.*, 2013). However, large amounts of milk left in the gland do have an impact on milk production rate as was shown by Penry *et al.* (2017). Krawczel *et al.* (2017) showed that there was no effect of a 0.48 kg / min removal strategy on SCC or milk production in an AMS.

The average milking interval for the cows in our study was 14.1 hrs., which is equivalent to a milking frequency of 1.7 milkings/cow/day. Robotic grazing systems tend to have longer milking intervals than confinement systems (Lyons *et al.,* 2013). The milking frequency in our study was lower than that reported by Lyons *et al.* (2017) who found an average of 2.38 milkings per day on eight Australian farms. There was, however, a large variation between farms with some farms similar to the farm in our experiment. Our study had lower milking intervals than what was found in a pasture based automatic milking systems by Shortall *et al.* (2018), where milking interval ranged from 16.1–16.4 hrs, or equivalently a milking frequency of 1.4 milkings per day. The research farm in our study had 86 milking cows on one robot, considerably higher than the eight farms average of 51 cows reported by Lyons *et al.* (2017) for grazing robotic farms with a maximum of 75 cows per robot. More cows per robot puts an extra time pressure on the robot and makes it more challenging to achieve higher milking frequencies.

Conclusion

Significant reduction in milking time and box time can be achieved by using a teatcup removal strategy of 30% (MFR30) and 50% (MFR50) of the rolling average milk flow-rate compared to 20% (MFR20) of the average flow-rate. This study showed that these removal strategies did not affect somatic cell score or milk production rate.

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References

Bruckmaier, R.M. and Hilger, M. (2001). Milk ejection in dairy cows at different degrees of udder filling. *Journal of Dairy* Research, 68(03): 369–376.

Burke, J.K., and Jago, J.G. (2011). Comparing somatic cell counts, production and milking durations of dairy cows when milked at two automatic cup-removal flow-rate thresholds. *Animal Production Science,* 51(10): 920–924.

Castro, A., Pereira, J.M., Amiama, C., and Bueno, J. (2012). Estimating efficiency in automatic milking systems. *Journal of Dairy Science*, 95(2): 929–936.

Davis, K., Jago, J., Wieliczko, R., Copeman, P., Bright, K., and Woolford, M. (2005). Factors influencing milk harvesting efficiency in an automatic milking system. In: *Proceedings of the New Zealand Society of Animal Production,* Napier, New Zealand, 271–275.

Edwards, J.P., Jago, J.G., and Lopez-Villalobos, N. (2013). Milking efficiency for grazing dairy cows can be improved by increasing automatic cluster remover thresholds without applying premilking stimulation. *Journal of Dairy Science,* 96(6): 3766–3773.

Krawczel, P., Ferneborg, S., Wiking, L., Dalsgaard, T.K., Gregersen, S., Black, R., Agenäs, S., Svennersten-Sjaunja, K., Ternman, E. (2017). Milking time and risk of over-milking can be decreased with early teat cup removal based on udder quarter milk flow without loss in milk yield. *Journal of Dairy Science,* 100(8): 6640–6647.

Lyons, N.A., Kerrisk, K.L., Garcia, S.C. (2013). Comparison of 2 systems of pasture allocation on milking intervals and total daily milk yield of dairy cows in a pasture-based automatic milking system. *Journal of Dairy Science,* 96: 4494–4504.

Lyons, N.A. and Kerrisk, K.L. (2017). Current and potential system performance on commercial automatic milking farms. *Animal Production Science,* 57: 1550–1556.

Penry, J.F., Endres, E.L., de Bruijn, B., Kleinhans, A., Crump, P.M., Reinemann, D.J., and Hernandez, L.L. (2017). Effect of incomplete milking on milk production rate and composition with 2 daily milkings. *Journal of Dairy Science,* 100(2): 1535–1540.

Shortall, J., Foley, C., Sleator, R.D., and O'Brien, B. (2018). The effect of dairy cow breed on milk production, cow traffic and milking characteristics in a pasture-based automatic milking system. *Livestock Science,* 209: 1–7.

A new method of measuring liner overpressure

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Abstract

We present a method of quantifying teatcup liner overpressure (OP) which is non-invasive, may be used during normal milking, and reflects the effects of liner, cow, milking machine settings and stage of milking.

Pulsation chamber vacuum was recorded as an amplitude-modulated carrier simultaneously with recording of vibration of the short milk tube (SMT) detected by a small vibration transducer coupled thereto. The frequency spectrogram of the vibration transducer signal showed a characteristic signature (validated by 1,000 frame/sec video with a transparent liner) indicative of milk flow. The pulsation chamber vacuum at which milk flow began corresponds to OP.

In a paired test of eight cows and two liners, a reference method (OP with limited pulsation (OP_{lp})) estimated the OP_{lp} difference between the two liners to be 3.1 kPa, $p < 0.05$, by t-test. Our method estimated the OP difference between the same liners at peak flow to be 4.4 kPa, $p < 0\ .005$, by repeated measurements model (SAS PROC MIXED).

Keywords: teatcup liner overpressure, milk flow detection, flow induced vibration

Introduction

A conceptually attractive means of characterising the forces applied to teat tissues is to use, as a baseline reference point, the differential pressure across the liner at which flow from the teat just begins or ceases. Mein and Reinemann (2014) called the point on the pulsation curve at which milk just begins to flow the 'Start of Milk Flow' (SMF), and the pulsation chamber vacuum at which this occurs 'Pulsation Chamber Vacuum at Start of Milk Flow' (PCV SMF). Clearly, during the maximum vacuum phase of pulsation (phase b as defined by ISO, 2007), as well as the late increasing vacuum phase a and early decreasing vacuum phase c, the pressure differential across the liner must be less than PCV SMF. If not, no milk would flow. With the net force on the teat-end favouring fluid accumulation, the teat-end will tend to develop congestion and edema. For successful milking, this tendency must be counteracted by pressure differential greater than PCV SMF during the minimum vacuum phase (phase d), as well as the late phase c and early phase a. In a typical milking system, in which phase d pulsation chamber pressure equals atmospheric pressure, the closing pressure differential across the liner during phase d will exceed the pressure at which milk just starts or stops flowing by an amount equal to PCV SMF. This excess pressure is named 'Overpressure' (OP).

The state of teat-end congestion or edema is dynamic, increasing within each milking phase as phase b continues. For this reason, measurements of overpressure must specify the dynamic nature of the forces on the teat. Overpressure (no pulsation) (OP_{np}) is determined when pulsation chamber (PC) vacuum is slowly increased, allowing congestion or edema to build up as the measurement is made. An example is the early study by Mein *et al.* (1987). Overpressure (limited pulsation) (OP_{lp}) is determined by slowly increasing vacuum level of

the pulsator vacuum supply line over a series of pulsations until milk flow just begins. An example is the 'OP Bucket' (OPB) study by Leonardi *et al.* (2015). OP (no subscript) would be determined where the start of milk flow is detected during phase a of normal pulsation.

Penry and Mein (2019) provide an explanation of OP as well as of liner compression (LC), (the compressive pressure, over and above the pressure of air in the pulsation chamber, applied by the liner to the teat apex). The advantage of using OP as a defining liner characteristic is that it is a biologically relevant indicator of LC but can be measured during milking. We now report a technique in which milk flow is detected by a miniature vibration transducer acoustically coupled to the short milk tube immediately below the teatcup shell. Milk flowing from the teat canal strikes the liner wall, inducing vibration of the liner wall. This vibration propagates along the liner and short milk tube at the speed of sound until it reaches the transducer, causing an electrical signal. For determination of overpressure, it is the timing (not the amplitude or frequency) of the start of this electrical signal in relation to the rise or fall of vacuum in the pulsation chamber that is of interest. If pulsation chamber vacuum is recorded simultaneously with the vibration signal, the vacuum at the instant of initial detection of vibration is PCV SMF.

Materials and methods

Control of pulsation phases a and c

For the instrumented teatcup, we replaced the generic pulsator with an arrangement of four normally closed solenoid valves, each having an adjustable flow control valve connected in series. Two of these valves in parallel connected the pulsation chamber to atmosphere, and the other two in parallel connected the pulsation chamber to the pulsator vacuum line. All four valves were controlled by a programmable logic controller. This arrangement allowed us to reduce the slope of the portions of phases a and c during which OP was to be determined, reducing the sensitivity of OP measurement to errors in determination of the time of milk flow start or stop. The effects of teat edema do not set in until about 0.5 sec. after liner opening (Williams, *et al.*, 1981) so we set the duration of the slow portion of phase a (during which milk flow was expected to begin) to end before this, choosing 0.25 sec. Edema likely began during phases b and c; not attempting to prevent this, we chose 0.35 sec for the slow portion of phase c.

Recording of Pulsation Chamber Vacuum and Liner Wall Vibration

The key information we extracted from our recordings of vibration and PC vacuum was the PC vacuum at the instant of vibration detection. This information was manually read from the graphic presentation generated by 'Raven' software (Bioacoustics Research Program, 2014). Data input to 'Raven' was in the form of two-channel WAV files, one channel representing vibration, and a second representing PC vacuum. We handled and processed the vibration signal as if it was an audio signal. The vacuum transducer's signal was multiplied by a constant 2 kHz sine wave, yielding a signal comprising a 2 kHz carrier amplitude modulated by PC vacuum, which could also be handled as an audio signal. Linearity of the vacuum recording was verified against a mercury manometer over the range of 0 – 50 kPa. For each of the two channels, Raven displays both an amplitude record and a frequency spectrograph.

The vacuum transducer was a solid-state analog transducer, protected by a small polyethylene bag and taped to the teatcup shell, connected by a short flexible tube to a tee inserted into the short pulse tube. The miniature, solid state, vibration transducer (BU-27135-000, Knowles Electronics, Itasca, Illinois 60143) was acoustically coupled to the short milk tube by aqueous gel and held in position by silicone elastic bands. Both were protected from ambient moisture by spray-on silicone conformable coating. The

attachment of the vibration transducer to the short milk tube and the connection of the vacuum transducer to the short milk tube are shown in Figure 1.

As confirmation that milk flow striking the inside of the liner barrel was the source of the short milk tube vibration signals we observed, we conducted a short confirmatory study in which milk flow and liner motion in a transparent teatcup were recorded by high speed (1,000 frames per second) video (Phantom v710, Vision Research, Inc., 100 Dey Road, Wayne, N.J. 07470) at the same time short milk tube vibration was recorded as described above. A single frame capture from the video is in Figure 2. To compare the OP values obtained by the vibration method with OP values by a previously reported method, we also measured OP_{lp} for the same liners and cows using the OPB method described by Leonardi *et al.* (2015). The OP_{lp} tests for each liner were run on the day immediately following the OP test for the same liner.

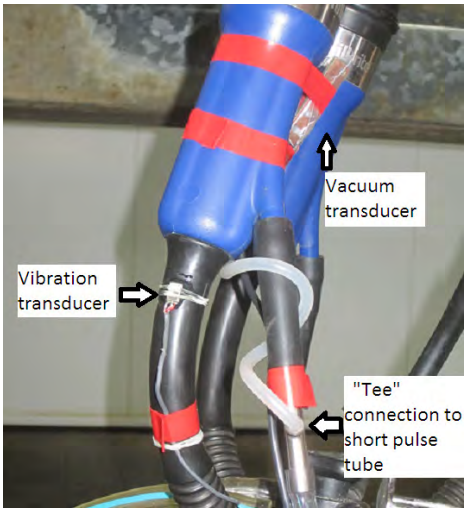


Figure 1. Arrangement of sensors for recording of short milk tube vibration and pulsation chamber vacuum. The vibration transducer used to detect flow-induced vibration is held in place with elastic bands and coupled to the short milk tube with aqueous gel

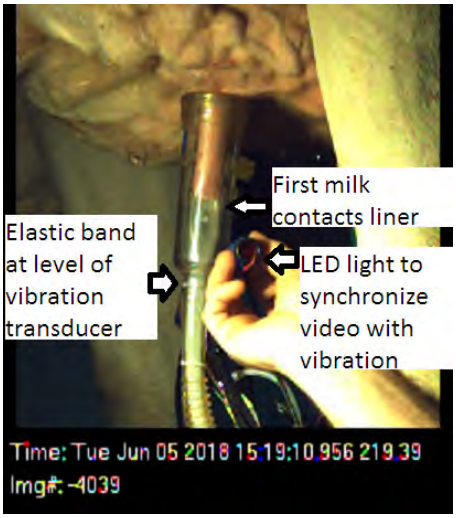


Figure 2. Single frame from Phantom video, taken at time 15:19:10.956. The liner is just beginning to open, and the spot of milk contact can be seen just beneath the teat. The operator is holding the LED light used to synchronize video with the 'Raven' record

Data Analysis

For each cow milking, the entire record of PC vacuum and SMT vibration was presented in Raven's graphic output. Figure 3 is an expanded record which includes only three pulsation cycles. Within each milking, numerous pulsation cycles were selected for analysis. We selected a series of approximately 10 consecutive pulsation cycles during the peak milk flow period. If the vibration signal during peak flow was not strong and easy to interpret, we selected a second group of consecutive cycles from the portion of the recording with the strongest signal. Finally, we selected for analysis approximately 10 pulsation cycles uniformly distributed throughout the milking. Data from all selected pulsation cycles was included in the analysis.

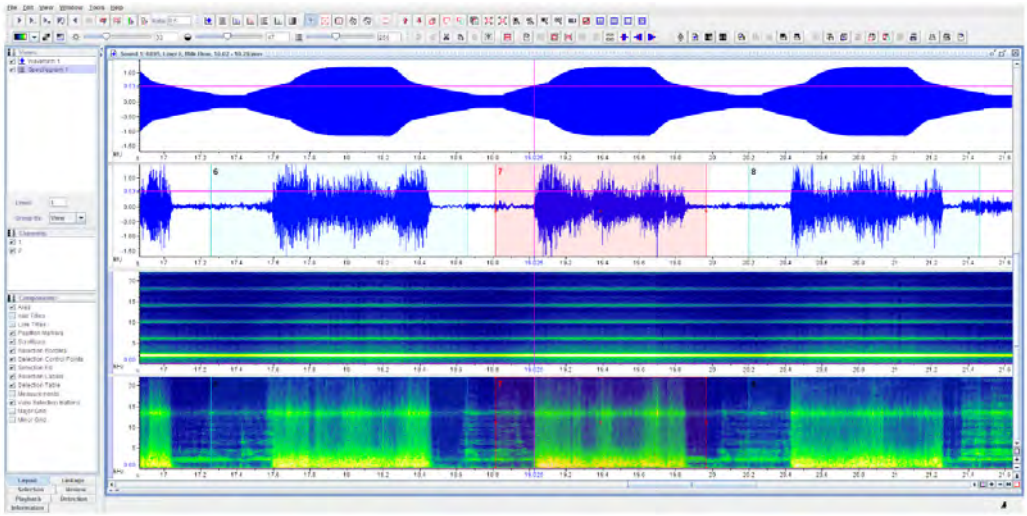


Figure 3. 'Raven' plot showing, from top to bottom, (1): pulsation chamber vacuum, (2): SMT vibration, (3): spectrogram of pulsation chamber vacuum signal (frequency on vertical axis, time on horizontal axis, brightness proportional to power level at that frequency and time). (4): spectrogram of vibration transducer output. Horizontal cursor indicates pulsation chamber vacuum at start of milk low, vertical cursor indicates time at start of milk flow.

For each analysed pulsation cycle we examined both the amplitude and the spectrographic record of the vibration signal to determine the time of flow start and stop. (The amplitude record gives a very clear time, and the spectrographic record allows some filtering out of non-flow signals such "squawks" from air leakage past the liner mouthpiece). At the moment of flow start or stop, the amplitude of the vacuum transducer signal was recorded, together with the amplitude during the preceding phase d (used as a zero-vacuum reference) and the amplitude during the following phase b (used as a vacuum line vacuum reference). PC vacuum at the start or stop of milk flow was then calculated by interpolation. Additionally, duration of milk flow within the pulsation cycle was calculated as the time difference between flow start and flow stop. The final data set consisted of OP at flow start (StartOP), OP at flow stop (StopOP), and flow duration (Duration) for each analysed pulsation, together with stage of milking, liner and cow. We tested two liners (designated 'F' and 'W'.) and eight cows. We divided each milking into five stages: 'Filling' (Stage 1) began immediately after cups on and included pulsations for which the duration of milk flow had not reached 0.5 sec, which we considered to represent teatcup not fully established in position on the teat or pre-letdown. 'Prepeak' (Stage 2) included pulsations thereafter until 'Peak' (Stage 3) flow began. After peak flow, we noted a 'Postpeak' (Stage 4) stage, which continued until flow duration fell below 0.5 sec, after which we denoted the 'Emptying' (Stage 5) stage.

The vibration data sets (StartOP, StopOP and Duration) were analysed by repeated measurements model (SAS Proc. MIXED) (SAS 9.4, SAS Institute, Cary, N.C.). The models were:

StartOP, StopOP, or Duration = cow + liner + stage + liner*stage + cow*liner

In addition to significance of the main effects, we tested the significance of each of the paired comparisons between cows, liners, stages, liners within stage and cows within liner, using the Tukey-Kramer method.

Each measurement of OP_{lp} was repeated three times for each combination of cow and liner and the three measurements were averaged and compared by t-test.

Results

Main effects for liner and stage are presented in Table 1. Least square means for liner within stage are plotted in Figures 4 - 6. Differing letters within stage indicate $P < 0.05$. We do not report here the effects of cow, and of cow within liner.

The OP_{lp} average values were significantly different ($P < 0.05$). The mean OP_{lp} across all cows for liner 'F' was 16.7 kPa and the mean OP_{lp} for liner 'W' was 13.6 kPa.

Table 1. Least Square Means and significance of differences for OP at flow start, OP at flow stop and flow duration

	StartOP		StopOP		Duration	
	Least Square Mean (kPa)	Different letters indicate differences P<0.05	Least Square Mean (kPa)	Different letters indicate differences P<0.05	Least Square Mean (sec.)	Different letters indicate differences P<0.05
Liner						
F	24.96	a	26.89	a	.550	a
W	25.01	a	24.02	b	.600	b
Stage						
1	33.29	a	37.06	a	.369	a
2	21.51	b	18.84	b	.724	b
3	18.85	b	15.11	c	.770	c
4	20.26	b	18.34	b	.723	b, c
5	31.01	a	37.93	a	.287	a

Discussion

Our method of determining overpressure by detecting flow-induced vibration of the short milk tube allowed us to determine the short pulse tube vacuum at both flow start (StartOP) and flow stop (StopOP) within pulsation cycle at any stage of milking. By the vibration method, we estimated the difference between StartOP's of liners 'F' and 'W' at peak flow as 4.39 kPa. The difference between the two liners for StopOP was also

4.39 kPa, whereas the 'OPB' method indicated an OP_{lp} difference of 3.1 kPa. The average across all cows of the estimates for both liners was 18.85 kPa for StartOP, and 15.12 kPa for StopOP. The OPB method will detect flow if the teat canal opens at any time during phase b, and this increased time for the viscoelastic properties of the teat to allow the canal to open might logically lead to OP_{lp} lower than StartOP. Our average value for OP_{lp} was 15.1 kPa. The difference between StartOP and StopOP is probably due to a combination of the effects of: time of flight (the sum of time for milk flow from teat end to liner wall and of time for vibration transmission from liner wall at the point of milk impact to the location of the vibration transducer); as well as hysteresis induced by the viscoelastic properties

both of teat tissues and of liner material. Both StartOP and StopOP are realistic indicators of liner/teat interaction; we suggest that either could be used for comparison with other liner/teat combinations.

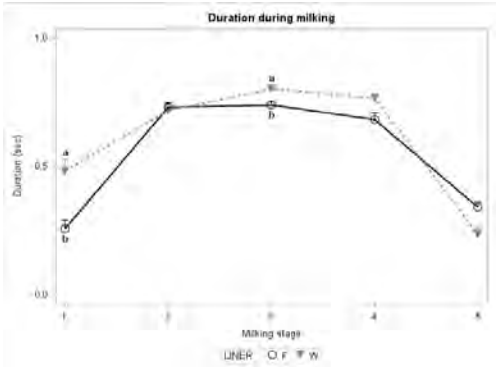


Figure 4. Flow duration, showing effect of liner and of stage of milking

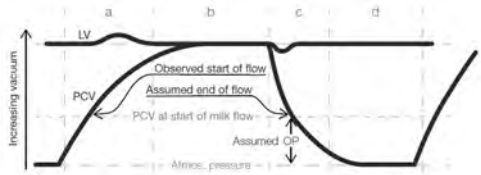
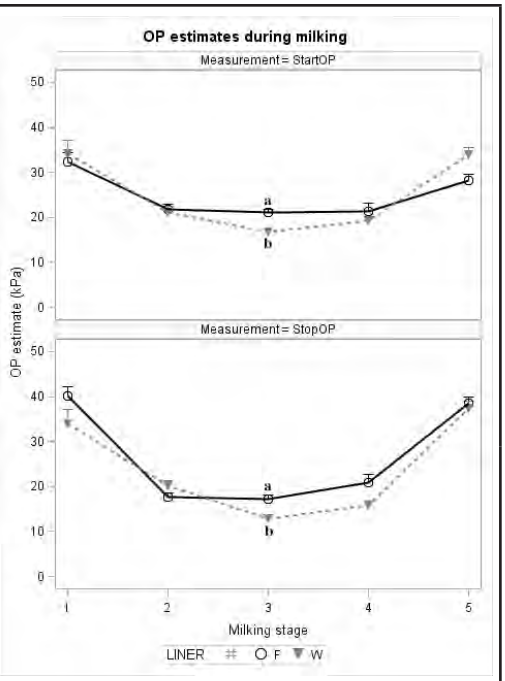


Figure 7. Illustration of OP and of pulsation phases, adapted from Penry and Mein (2019)



Figures 5 (upper) and 6 (lower). Overpressure at start and stop of milk flow, showing effect of liner and of stage of milking

The effect of stage of milking on either StartOP or StopOP was clear, and the trend for either was for a minimum value during peak flow, with higher values nearer the beginning or end of milking. There is a symmetry to these curves, but the causes of higher OP near the start vs end of milking are probably different. Leonardi *et al.* (2015) measured OP_{lp} one minute after unit attachment, and then repeated the measurement at one minute intervals for a total of four measurements. They found a significant reduction in OP_{lp} with time, and this would correspond with our findings at the earlier ('Pre-peak' and 'Peak') portions of our measurements. They mentioned possible causes for the decrease as: subtle changes in the position of the teat within the liner, small changes in teat sinus pressure, or a slight relaxation of teat end musculature. We agree with this list of possible causes for the decrease in OP in the early stages of milking. The increase in OP later in milking might again relate to teat sinus pressure changes or changes in position of teat within the liner. A likely additional factor in the later stages of milking results from the commonly observed shift of the liner towards the teat base. The accompanying development of vacuum in the teat sinus results in a progressive increase in congestion of teat tissues and thickening of the teat walls. OP rises as the teat-apex becomes harder and thicker because the liner walls must bend further as they collapse around the teat-end.

The duration of milk flow within a pulsation cycle is a parameter not determined by previously reported systems for OP measurement. Although the initial purpose of detecting the onset or cessation of flow by monitoring SMT vibration was to determine the pulsation vacuum at which milk flow started or stopped (StartOP or StopOP), knowing both the start and the stop times also gives the duration of flow, and this parameter is of interest. (For clarity, it needs to be remembered that if the shape of the pulsation waveform is known, Duration, StartOP and StopOP are interrelated and, as can be seen in Figure 7, knowing any two allows calculation of the third). Duration less than the maximum observed during peak flow indicates that for some portion of the time during which liner forces on the teat should allow milk flow through the teat canal, milk does not flow. Considering the factors that might affect StartOP and StopOP, it is logical to surmise that a likely cause of short duration near the start of milking might be inadequate letdown or poor placement of the teatcup on the teat. Either of these causes would indicate a need for adjustments in milking routine. The likely cause near the end of milking is simply that quarter nearing the end of milking, with the result that rate of replacement of milk into the teat sinus is slower than the rate of milk withdrawal through the teat canal.

Conclusions

Detection of milk flow within pulsation cycle by monitoring of short milk tube vibration allows determination of overpressure in a normal milking setup with unmodified liners. This will allow comparison of liners by a parameter that reflects the forces resulting from the interaction of liner with teat. This measurement could also be made using a standardised artificial teat incorporating a teat canal/milk flow analog that responds to liner compression. Further, there is a potential to make this measurement under field conditions and to use the results to adjust selection of liners and adjustment of machine parameters in the way most beneficial to the specific herd involved. With real-time measurements using this technique, it could be possible to adjust machine operating parameters interactively during milking. An even simpler measurement, of flow duration, does not require monitoring of the pulsation waveform so only a simple vibration transducer is needed. Knowledge of duration would allow generation of an automatic alert if the machine is not interacting with the teat as expected and would also allow determination of end of milking without needing to monitor milk flow.

Our recovery of useful data from the short milk tube vibration and pulsation vacuum records was quite laborious. Automated real-time analysis of the data stream is a logical next step, and it is not unrealistic to expect that this could rely on embedded sensors and milk flow detection algorithms. In the context of precision livestock farming, this would allow end of milk flow sensing, automatic control of machine parameters, and fault detection within the milking process based on feedback of milking information within the time constant of single pulsation cycles.

References

Bioacoustics Research Program. (2014). Raven Pro: Interactive Sound Analysis Software (Version 1.5) [Computer software]. Ithaca, NY: The Cornell Lab of Ornithology. Available from http://www.birds.cornell.edu/raven.

International Standards Organization (2007). ISO 3918 (2007) Milking machine installations – vocabulary. International Organization for Standardization, Geneva, CH. 35 pp.

Leonardi, S., Penry, J.F., Tangorra, F.M., Thompson, P.D., and Reinemann, D.J. (2015). Methods ofestim ating liner compression. *Journal of Dairy Science* 98, 6905–6912.

Mein, G.A., and Reinemann, D.J. (2014). *Machine Milking, 1*: 148.

Mein, G.A., Williams, D.M., and Thiel, C.C. (1987). Compressive load applied by the teatcup liner to the bovine teat. *Journal of Dairy Research,* 54: 327–337.

Penry, J.F. and Mein, G.A. (2019). Teatcup action: what is meant by 'liner compression' and 'overpressure'? In: Proceedings 58th Annual Meeting of National Mastitis Council, Savannah, GA, USA, pp. 143–144.

Williams, D.M., Mein, G.A. and Brown, M.R. (1981). Biological responses of the bovine teat to milking: information from measurements of milk flow-rate within single pulsation cycles. *Journal of Dairy Research*, 48: 7–21.

Predicting somatic cell counts in an automatic milking rotary using conductivity and generalised additive models

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Abstract

This study investigated if conductivity sensor data from an automatic milking rotary (AMR) could be used for explaining composite somatic cell count (CMSCC). By predicting somatic cell counts for individual cows, monitoring of udder health can be improved by reducing both labour and costs for the farmer. During a period of eight weeks, milk samples from 380 Holstein- Friesian cows milked in an AMR were analysed once weekly for composite somatic cell count (CMSCC). Regularly recorded sensor data at quarter and composite level from the herd management system was stored and used as input to generalised additive models (GAM) used in the analyses. Several new conductivity variables were created combining quarter conductivity. Furthermore, past period values, i.e. lags of up to seven days (14 milking sessions), were added to the variables. A Multivariable GAM was fitted in order to compare the importance of the potential predictor variables as well as model performance. The variance in conductivity between quarters, one milk session before the CMSCC sample event, was the most important variable. Conductivity variables from combined quarters are suggested to be important in describing CMSCC. We conclude that using data from only six milk sessions before the CMSCC sample event is sufficient to obtain a relatively high degree of explanation (R^2_{adj} = 0.78). To evaluate the practical applicability of these results, we recommend investigating whether it is possible to predict CMSCC using GAM.

Key words: automatic milking, udder health, somatic cell count, quarter conductivity

Introduction

Somatic cell count (SCC) is a common method for monitoring udder health in dairy herds (Kitchen, 1981; Schukken *et al.*, 2003; Sharma *et al.*, 2011), since monitoring SCC can be a good tool for identifying intramammary infections in individual cows (International Dairy Federation, 2013). To monitor SCC levels at the cow level, farmers can sample their cows either through the monthly sampling of their local milking organisations or with on-farm tests like the Californian mastitis test (CMT) or more precisely in fluoro-opto-electronic instruments either used in a standalone device or integrated in the milking system. Depending on the method, more frequent sampling of individual cows will increase costs or workload for the farmer. Therefore, predictions of SCC level of individual cows could be both a valuable tool and powerful complement to the existing methods. To our knowledge, very few studies have attempted to describe SCC patterns using sensor data to complement traditional direct measurements of SCC (Sitowska *et al.*, 2017; Ebrahimie *et al.*, 2018).

The objective of this study was to investigate the possibility of using the existing conductivity sensor data from an automatic milking rotary (AMR) to describe the SCC with a generalised additive model (GAM). The outcome of this study could potentially be used as supplementary information for the farmer between SCC measurements.

Materials and methods

Data Collection

Milk samples from 380 Holstein-Friesian cows milked in an automatic milking rotary (DeLaval AMR) were collected once weekly during eight weeks. The samples were analysed for composite milk somatic cell counts (CMSCC) in a laboratory in Jena, Germany using a Fossomatic 7, DC 600 system (ISO/IEC, 2005). Animal information together with milking data on quarter level from the trial period were stored and further referred to as milk data. The data comprised quarter conductivity and at the cow composite level days in milk (DIM), lactation number (LN) and cow number.

Data Preparation

Cows not included in the weekly CMSCC sampling were removed from the milking data as were all milking events for cows during the first week of lactation. Furthermore, CMSCC observations that did not include a complete setup of variables for 14 milking sessions before the CMSCC sampling event were also removed. Remaining cows were placed into lactation groups 1, 2, and ≥ 3. Quarter conductivity values considered not biologically plausible (i.e. below 3 mS / cm and above 10 mS / cm) were removed from the milking data. The AMR contains 24 milking bails and thus 96 milk meters, registering all milking data at the quarter level. Conductivity measurements between the 96 milk meters were equalised using an offset value that was created for each milk meter. The offset was created by dividing the overall mean conductivity value of quarter *i* by the overall mean conductivity value from the milk meter *j*, corresponding to quarter *i* from three months data (one month prior to the first sample). The offset values for each milk meter were then multiplied by the corresponding conductivity values, adjusting the conductivity level according to the offset. Several new variables were created from the quarter conductivity variables (Table 1). Past-period variables (lags) were created to evaluate how predictive the variables could be up to seven days (14 milking sessions) before the actual CMSCC sample. The CMSCC values were transformed to a log10 scale, henceforth referred to as log10CMSCC. In total, < 1% of the data was removed due to cleaning. To avoid multicollinearity, a variance inflation test (VIF) was performed within variable among days lag. Variables with VIF > 8 (Fox & Monette, 1992) were removed from further analysis.

This was only valid for the variable conductivity max where the variables with day lag 2, 5 and 12 were removed. A complete list of the potential predictor conductivity variables and the milking session lags can be found in Table 1. All data cleaning and statistical analyses were performed in the program R using the 'mgvc' for model development (R Development Core Team, 2018).

Multivariable Generalised Additive Models

Two multivariable models were fitted: model_0:7, using the 42 variables with time lags from 0–14 milk sessions (i.e. 7 days) and model_0:3, using 19 variables with time lags from 0 - 3 days (i.e. six milk sessions) before the CMSCC sample event. The two GAM (Hastie & Tibshirani, 1990) models, containing multiple potential predictors in each model were fitted as smooths, i.e. non-parametric spline functions, not forcing linearity between the predictor and the outcome. The response variable was log10CMSCC, and LN, DIM and Cow were confounder variables according to:

$$y_i = \beta_0 + LN\beta_{LN} + DIM\beta_{DIM} + \alpha_{Cow} + \sum_{j=1}^{p} f_j(X_{ij}) + \epsilon_i, \quad (1)$$

$$\alpha_{Cow} \sim N(0, \sigma^2_{Cow}), \epsilon_i \sim N(0, \sigma^2_{\epsilon}).$$

Table 1. Explanation of the potential predictor conductivity variables used in model fit and number of milk session lags

Variable (mS/cm)	Explanation	Milking session lag
Diff.quarters	Highest conductivity value minus lowest conductivity value within cow and milking session	{0 1 2 3 4 5 6 7 8 9 10 11 12 13 14}
Max	Highest conductivity value (quarter) within cow and milking session	{0 1 3 4 6 7 8 9 10 11 13 14}
Var	Variance in conductivity values between quarters within cow and milking session	{0 1 2 3 4 5 6 7 8 9 10 11 12 13 14}

The smoothing parameter estimation method used in both models was restricted maximum likelihood (REML). The adjusted coefficient of determination (R^2_{adj}) was used for evaluation of model performance. The corrected Akaike information criterion (AIC), described by Wood *et al.* (2016), was used for model comparison.

Results

Effects of Variables

The results showed that the strongest predictor variable associated with CMSCC was variance in conductivity values between quarters one milk session before CMSCC sample event (model_0_7, $P < 0.001$, $\alpha = 0.05$). The relationship between variance in conductivity between quarters and CMSCC was found to be nonlinear and mainly positive.

Models

The difference in R^2_{adj} between model_0:7 and model_0:3 was very small (0.78 for model_0:7 vs 0.776 for model_0:3). Comparing models using AIC showed the same trend (297 for model_0:7 vs 322 for model_0:3).

Discussion

The results indicate that it is possible to describe CMSCC relatively well (R^2_{adj} 0.78) using GAM with relatively limited amount of conductivity sensor data from an AMR. Using data from 3-7 days before the CMSCC sampling event did not affect the performance of the models much. GAM are flexible and can provide information regarding both linear and nonlinear relationships between the predictor and the response variables (Hastie & Tibshirani, 1990). The results indicate that GAM are well suited to explain the nonlinear relationship between different conductivity variables and CMSCC.

Previous studies have shown that using traits such as combined quarter conductivity rather than the maximum conductivity alone improved the specificity in a mastitis detection model with almost 15% (Norberg *et al.*, 2004). The degree of explanation of the models could partly be explained by the inclusion of the different conductivity variables, describing different traits such as difference or variance in conductivity or the maximum conductivity of a quarter. Variance in conductivity between quarters one milk session before the CMSCC sample event had the strongest association with CMSCC among the potential predictor variables.

The relationship between SCC and conductivity is suggested to be positive (Hamann & Zecconi, 1998), i.e. as conductivity increases or decreases, so does SCC. According to our findings, displayed by the trend lines found in Figure 1, the relationship between variance in

conductivity between quarters and SCC is partly positive up to variance between quarters of 0.5. For variance in conductivity above 1.5, the difference in trend lines between milking sessions could possibly be explained by the few data points on the x- axis. Although the slope for the relationship is not clear, it could be concluded that the relationship between variance in conductivity and SCC is not linear.

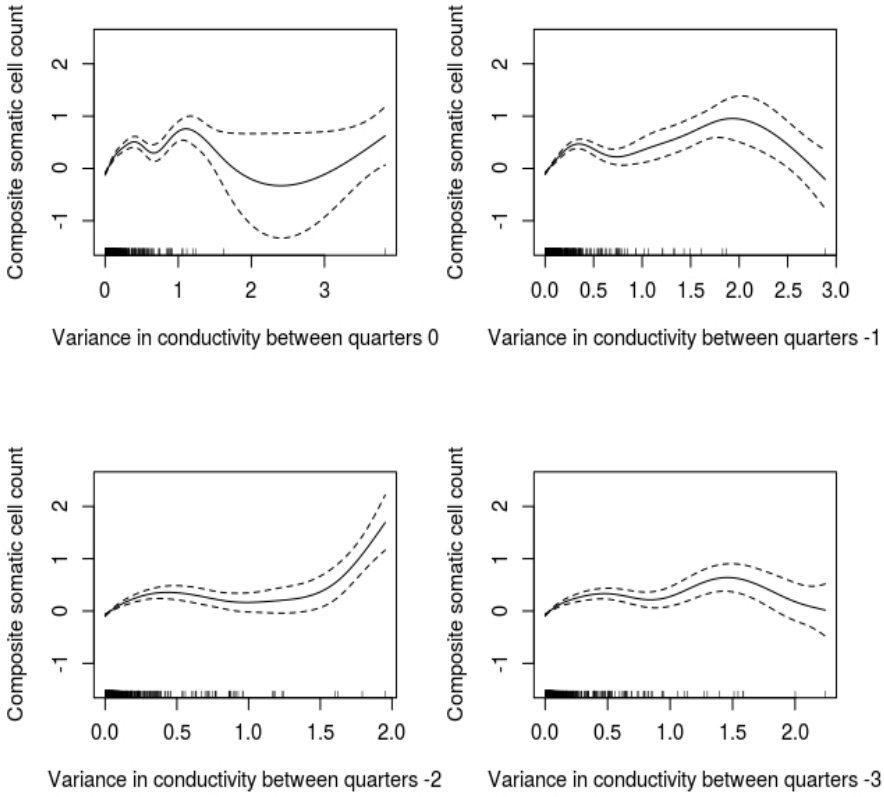

Figure 1. The partial effects of variance in conductivity bwetween quarters at the same milking session as the composite milk somatic cell count (CMSCC) sampling event (upper right) and -1,- 2 and -3 milking sessions before the sampling event. The pointwise 95% confidence interval is shown by the dashed lines. The vertical lines on the *x*-axis show the individual datapoints of variance in conductivity. The *y*-axis shows the log10CMSCC

Quarter conductivity alone has been stated to be a poor predictor of mastitis (Kamphuis *et al.*, 2008; Khatun *et al.*, 2017), and within-cow comparison of quarters is often recommended (Hamann & Zecconi, 1998). Our results support this theory, suggesting that combined conductivity variables are important in explaining CMSCC. Furthermore, conductivity observations close in time to the CMSCC sampling event were more important in explaining the CMSCC than were observations made several days before sampling. This is in line with the finding of Nielen *et al.* (1995), whereby the conductivity difference was largest for the milking during which the clinical mastitis was observed compared with the two milkings before the observation. Using only a limited amount of variables close to the sample event did not affect the degree of explanation much.

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References

Ebrahimie, E., F. Ebrahimi, M. Ebrahimi, S. Tomlinson, and K.R. Petrovski. (2018). Hierarchical pattern recognition in milking parameters predicts mastitis prevalence. *Comput. Electron. Agric.*, 147: 6–11.

Fox, J., and G. Monette. (1992). Generalized collinearity diagnostics. *J. Am. Stat. Assoc.*, 87: 178–183.

Hamann, J., and A. Zecconi. (1998). Evaluation of the electrical conductivity of milk as a mastitis indicator. *Bull.*, 334: 5–22.

Hastie, T., and R. Tibshirani. (1990). Generalized Additive Models. Chapman and Hall, New York.

International Dairy Federation. (2013). Guidelines for the use and interpretation of bovine milk somatic cell count.

ISO/IEC. (2005). General requirements for the competence of testing and calibration laboratories.

Kamphuis, C., R. Sherlock, J. Jago, G. Mein, and H. Hogeveen. (2008). Automatic Detection of Clinical Mastitis Is Improved by In-Line Monitoring of Somatic Cell Count. *Journal of D*airy Science, 91: 4560–4570.

Khatun, M., C.E.F. Clark, N.A. Lyons, P.C. Thomson, K.L. Kerrisk, and S.C. García. (2017). Early detection of clinical mastitis from electrical conductivity data in an automatic milking system. *Anim. Prod.* Sci., 57: 1226–1232.

Kitchen, B.J. (1981). Review of the progress of dairy science: Bovine mastitis: Milk compositional changes and related diagnostic tests. *J. Dairy Res.*, 48:167–188.

Nielen, M., Y.H. Schukken, A. Brand, S. Haring, and R.T. Ferwerda-Van Zonneveld. (1995). Comparison of Analysis Techniques for On-Line Detection of Clinical Mastitis. *Journal of D*airy Science, 78: 1050–1061.

Norberg, E., H. Hogeveen, I.R. Korsgaard, N.C. Friggens, K.H.M.N. Sloth, and P. Løvendahl. (2004). Electrical Conductivity of Milk: Ability to Predict Mastitis Status. *Journal of D*airy Science, 87: 1099–1107.

R Development Core Team. (2018). R: A Language and Environment for Statistical Computing. Accessed March 5, 2019. http://www.r-project.org.

Schukken, Y.H., D.J. Wilson, F. Welcome, L. Garrison-Tikofsky, and R.N. Gonzalez. (2003). Monitoring udder health and milk quality using somatic cell counts. *Vet. Res.*, 34: 579–596.

Sharma, N., N.K. Singh, and M.S. Bhadwal. (2011). Relationship of somatic cell count and mastitis: An overview. *Asian-Australasian J. Anim. Sci.*, 24: 429–438.

Sitowska, B., D. Piwczyński, J. Aerts, M. Kolenda, and S. Özkaya. (2017). Detection of high levels of somatic cells in milk on farms equippedwith an automatic milking system by decision trees technique. Turkish *J. Vet. Anim. Sci.*, 41: 532–540.

Wood, S.N., N. Pya, and B. Säfken. (2016). Smoothing Parameter and Model Selection for General Smooth Models. *J. Am. Stat. Assoc.*, 111: 1548–1563.

At-market sensor technologies to develop proxies for resilience and efficiency in dairy cows

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Abstract

We hypothesise that at-market sensor technologies can be used to develop proxies for complex traits such as resilience and feed efficiency (FE). This was tested by comparing variables describing sensor data patterns ("curve-parameters") from resilient or FE cows with non-resilient or non-FE cows. Sensor data included data from weighing scales, activity (steps) and rumination activity from neck collars, and milk production from the parlour or the milking robot. Curve-parameters were calculated for each sensor for each lactation for which data was available and included the mean, standard deviation (std), slope, skewness, and the autocorrelation. Data originated from a Wageningen Research farm, and included data from 1,800 cows with calvings between 1995–2016. During this time frame, there were 98 lactations with sufficient feed intake recordings to compute FE at lactation level (DMI (kg) / milk yield (kg)), and to rank them accordingly. The 1,800 cows that could be ranked according to their lifetime resilience (ability to re-calf in combination with the number of health and insemination events) based on scores for each of the, in total, 5,771 lactations. Subsequently, the 20% or 10% most and least FE or resilient lactations, respectively, were selected. Curve-parameters of these selected lactations were compared. Results imply that using a single sensor, or a single curve parameter, is likely to be insufficient as a proxy for resilience of efficiency. Future research should focus on studying which combination of curve parameters and sensors are most informative as proxy for these two complex traits.

Keywords: resilience, feed efficiency, precision livestock farming, proxies

Introduction

After the Second World War, the animal production sector faced the challenge to satisfy a consumer market that demanded animal products in abundance and at low cost (Oltenacu & Algers, 2012). A combination of improved management, better feed and successful genetic selection on improved production resulted in the dairy industry being able to more than double the milk yield in many countries over the past 40 years (Oltenacu & Algers, 2012). For example, in the Netherlands, the average yearly milk production increased from 4,200 kg per cow in the 1960's to 9,100 kg per cow in 2018 (CBS, 2018). However, the increase in milk yield was accompanied by a decline in reproduction performances, an increase in health disorders, and a decline in longevity of dairy cows (Oltenacu & Algers, 2012). Moreover, public perception of animal production changed, with increasing concerns around animal welfare. This combination introduced an international interest in novel traits that improve fitness and health of dairy cows (Egger-Danner *et al.*, 2015; Oltenacu & Algers, 2012). Two of these traits gaining interest are efficiency and resilience. Efficiency is often expressed as feed efficiency (FE), and is of great interest for increasing profitability, as well as reducing the environmental footprint of animal production systems (Savietto *et al.*, 2014). Resilience is the ability of animals to be minimally affected in their functioning by an environmental perturbation, or to rapidly return to their normal level of functioning (adapted from Colditz & Hine (2016)). Despite the increasing interest in these traits, breeding for them is hampered by the lack of phenotypic information. Direct inclusion of feed intake in dairy cow breeding goals, for example, is not possible due to the costs associated with acquiring individual animal feed intake measurements on a large scale (Veerkamp, 1998).

The adoption of sensor technologies by dairy farmers is increasing (Steeneveld *et al.*, 2015; Borchers & Bewley, 2015). Farmers are adopting technologies that are deployed for the detection of specific health or fertility events (e.g. heat or mastitis), or that monitor important performance traits (milk yield or SCC). These sensor technologies generate high-frequency repeated measures, e.g. locomotor activity or rumination activity of individual animals. This means that instead of having snapshots of relevant events during a cow's lifetime (e.g. a mastitis event recorded by the farmer or veterinarian), we now have access to a continuous time-series of the cow's status. With these continuous measurements, cows can serve as their own control and allow precise herd level corrections when detecting outliers. Many disease detection models use the concept that disease occurrence is expected in case sensor measurements deviate from the expected values for that cow (e.g.,Jensen *et al.*, 2016; Miekley *et al.*, 2012), and therefore focus on the generation of true positive alerts. However, the specific feature of sensor technologies to monitor continuously make them also interesting for phenotyping animals for complex traits such as resilience and efficiency, and with that provide input for breeding programs. To our knowledge, so far, little to no attention has been paid for the possible use of sensor data in this regard.

As a first step in finding out whether these sensor technologies can be used to develop proxies for resilience and efficiency, we studied whether the data patterns were different between resilient (or efficient) and non-resilient (or inefficient) cows. This was done by comparing sensor data patterns between the 10–20% most and least resilient or efficient cows, respectively.

Materials and methods

Data

Data originated from the Dairy Campus, a Wageningen Research farm, and included data from 1,800 cows, totalling to 5,771 lactations, with calvings between 1995–2016. All of these cows were culled at the end of the data collection period. Over this time period, data were collected with a number of sensor technologies. Activity (steps) and rumination activity were monitored through SRC-tags (via Lely Industries, Maassluis, the Netherlands). Data from these tags were available from October 2007 onwards. The barn of this research farm was split into two sections: one with four groups of approximately 64 cows that were milked and weighed in milking robots (Lely Industries, Maassluis, the Netherlands), and one where cows were milked twice daily in a conventional milking parlour where live-weight was recorded before entering the parlour. Cows were allocated to groups based on research requirements, and could therefore be milked part of the time in one of the robots and part of the time in the parlour. In the section where cows were milked in the parlour, two subsections were equipped with roughage intake control (RIC) bins (Insentec, Marknesse, the Netherlands). Feed trials were common on this research farm, ensuring detailed measures of individual feed intake. For the current study we could use feed intake (DMI (in kg) / cow / day) records from one of the feed trials, where feed intake was monitored throughout entire lactations. All inseminations and health events (disease cases and treatments) were recorded in the farm management system.

Definitions for Resilience and Efficiency

In the current study, efficiency was expressed as FE, which was computed at lactation level as total input (DMI, in kg) over total output (milk yield, in kg). To be eligible for this FE computation, cows were required to have at least one RIC recording per week, for a minimum of 36 subsequent weeks. Due to the experimental setup, the selection did not include heifers lactations, but was restricted to lactations from 2nd – 7th parities.

Friggens & De Haas (2019) stress the importance of having an operational reference measure of resilience when developing a proxy for this trait. They suggest to use the within-cow variance associated with a relevant time-series of measures, which needs to be of sufficiently high-frequency to capture the variance due to perturbations. One option for measures against which to validate these resilience proxies include the ability to re-calve, assuming that impaired resilience will negatively impact reproduction performance (Friggens & De Haas, 2019). It is this option that we explored further in this study. To reflect how good (or bad) this ability was compared to herd mates, a point system was introduced based on a cow's lifetime. This point system included four aspects on top of 500 points for each calving:

- age at first calving compared to the herd average. Bonus points were given in case the age at first calving was lower than the herd average, and minus points in case this age was higher. One (bonus or minus) point was assigned for each day difference from the herd average. Bonus or minus points for this aspect were only assigned for first parity lactations;
- calving interval compared to the herd average. Bonus points were assigned in case the interval was shorter than the herd average, and minus points in case this interval was longer than the herd average. One (bonus or minus) point was given for each day difference from the herd average, where calving interval is the interval between the previous calving and the current calving. As such, points for this aspect were only assigned for second parity lactations and up;
- number of inseminations: because data on inseminations were incomplete and because poor fertility was also reflected in aspect two (calving interval), only inseminations carried out in the final lactation were taken into account in this third aspect. We applied 25 minus points in case culled cows were inseminated, assuming that the farmer planned to keep this cow but it was involuntarily culled due to fertility issues.
- number of events. Minus points were assigned to each event day, excluding preventive events, e.g. hoof trimming. Also inseminations and calvings are ignored since these events are already accounted for in aspect two and three. For each day during the lactation that a cow was curatively treated, one point was subtracted from the score. Moreover, because culling in an early stage after calving was assumed to be involuntary and could mask health problems that were not treated on-farm, one point was subtracted for each day the cow was culled before day 100 after calving. So, in case a cow was culled at 40DIM, 60 points were subtracted from the total score for the last calving.

Cows, or lactations in case of FE, were ranked according to their resilience or efficiency score.

Retrieving curve parameters

For each sensor (activity, rumination activity, milk yield, and live-weight), within-day measurements were aggregated to daily values. These daily values were made relative to the herd mean, and subsequently we summarised these relative values into "curve-parameters" at lactation level (Figure 1). These curve-parameters involved the mean, and autocorrelation (lag1) of the relative curve of each cow (red line; Figure 1), and the slope, skewness, and standard deviation of the regression line through this relative curve of each cow (light blue line; Figure 1). These curve parameters were computed for all lactations (for FE and for resilience) for which we had a sufficient amount of data (at least 200 days with data during 1 – 300 DIM). For resilience only first lactation curves were compared, assuming that these will be more useful to investigate differences between resilient and non-resilient cows than e.g. last lactation curves. For efficiency, which is currently purely calculated on a lactation basis, lactation curves were compared for the lactations for which efficiencies were calculated.

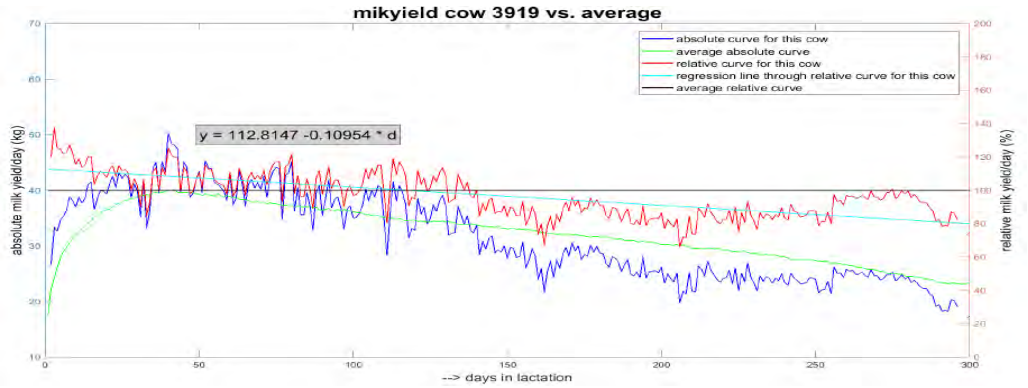

Figure 1. Assessment of curve parameters based on the relative curve (red line), or its regression line (light blue line) of a cow. The absolute values of the cow are in dark blue, the absolute herd mean values in green, and the relative herd mean values in black

Statistical analyses

The 10% or 20% most and least resilient cows or FE lactations, respectively, were selected and curve-parameters of these selected lactations were compared between these two groups.

Results and discussion

A FE score was computed for 98 lactations, with an average of 0.79 kg DM/kg milk, and a range of 0.48–1.19 kg DM/kg milk. A resilience score was computed for 1,800 cows with 5,771 lactations, with an average of 1,518 points and a range of 31–6,031 points. Figure 2 demonstrates a distribution plot for both traits (where the scores were classified into ten categories, each category having roughly 600 points for resilience and 0.11kg for FE), indicating that scores for these traits are not normally distributed. Particularly for resilience the distribution was skewed to the left.

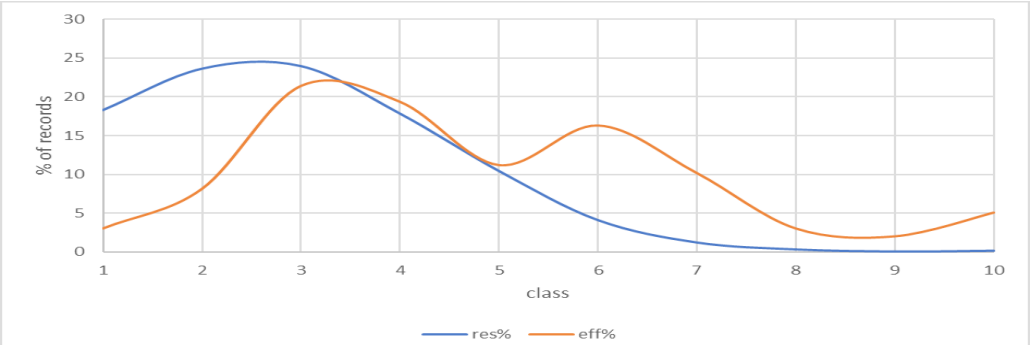

Figure 2. Percentage of values of the datasets for resilience (blue line) and feed efficiency (orange line), divided into 10 classes based on the range of values

Unfortunately, there were limitations with the data and, in particular, with the feed intake data. Feed intake was not recorded on a daily basis during an entire cow's lifetime, but only during feeding trials. Because of this limitation, we lacked feed intake data from heifers (since they were not included in feeding trials), but even more so, we also lacked information on feed intake over lactations from the same cow. Consequently, we were limited to lactation FE and have ignored other output than milk production, particularly

growth which certainly should be taken into account when comparing heifer efficiencies with cow efficiencies. In contrast, resilience was computed based on information on an entire cow's lifetime, but our scores are based on preliminary assumptions that need to be investigated further. Ability to re-calve as an indication for resilience suggests that resilience on a lactation basis is decreasing when an animal is aging, since the percentage of re-calvers is highest for heifers and gradually decreases thereafter. Moreover, production levels do influence a farmer's culling decisions, and thus, low producing cows may be unable to express their true resilience and be negatively affected in our resilience scoring system. Preferably, a resilience score should be unbiased by production and we need to determine methods to avoid or remove production effects. It would be of great interest to study whether cows that are FE are also resilient, but we were unable to do so because of FE being limited to lactation level. Future research should think of a definition of efficiency in absence of feed intake recordings.

Table 1 summarises the mean values (and their range) for the computed curve parameters for the 20 (20%) resp. 25 (10%) most and least FE or resilient cows, respectively. Not surprisingly, the group of lactations with the lowest score for FE has a lower mean milk production that those that belong to most FE. Moreover, the least FE lactations appear to be from cows that are, on average, heavier, less active and have a lower rumination activity than those that belong to the most FE lactations. However, there is an overlap in mean value for all sensors between these two groups. When looking at resilience, the difference in average daily milk production between the most and least resilient cows is not that pronounced as for FE. In fact, the difference between the two groups of resilience is, generally speaking, less pronounced overall. Whether this difference between groups is truly less pronounced should be studied in more detail: for the current study we applied a point system for four aspects to define resilience. But the value for bonus or minus points within each of these aspects was chosen intuitively. We have not yet conducted a sensitivity analysis to study whether the resilience ranking is robust (that is, independent from the value assigned to bonus or minus points). Future research should verify this. Moreover, we did not have sensor data from before October 2007, and therefore there might have been some bias in the selection of informative lactations.

The current study only computed curve parameters for the first lactation (resilience) or the lactation for which FE could be determined, and results imply that there is a large overlap between the curve parameters of the two groups of cows. However, a recent study reported on the utilisation of sensor information as indicators for resilient cows (Van Dixhoorn *et al.*, 2018). During that particular study, Van Dixhoorn *et al.* (2018) tested different sensor data properties from sensors monitoring activity, behaviour, and rumen and ear temperature. Data properties from these sensors recorded during the period from up to two weeks *before* calving were used as predictor for a total deficit score. This deficit score summarised the health status of a cow up to six weeks after calving, and was used as proxy for resilience. The study demonstrated that sensor data recorded during the dry period was informative for a resilience proxy after calving. Although Van Dixhoorn *et al.* (2018) included a limited number of cows (n = 20) and used a short-term resilience proxy (transition period), results from their study suggest that taking into account curve parameters from the previous lactation and particularly the dry period may be informative for lifetime resilience and lactation FE. This would also mean that sensor data should be collected during the dry period too, which is currently not standard procedure on commercial dairy farms.

Table 1. Mean values (and their range) for five curve parameters based on sensor data patterns from the most (highest) and least (lowest) feed efficient or resilient cows, including the absolute number of lactations

Sensor	Efficiency				Resilience			
Curve parameter	Number of lactations		Mean (range)		Number of lactations		Mean (range)	
	Highest	Lowest	Highest	Lowest	Highest	Lowest	Highest	Lowest
Milk production								
Mean	20	20	105.6 (93.4 - 126.5)	61.0 (46.9 - 72.4)	25	25	82.4 (56.4 ± 104.9)	87.1 (53.4 - 114.6)
Autocorrelation (lag1)	20	20	0.7 (0.4 - 0.9)	0.8 (0.2 - 1.0)	25	25	0.7 (0.3 ± 0.9)	0.8 (0.5 - 1)
Standard deviation	20	20	12.7 (7.0 - 19.1)	12.0 (6.0 - 26.6)	25	25	8.7 (5.2 ± 14.4)	9.3 (6.1 - 15.8)
Slope	20	20	-0.0 (-0.2 - 0.1)	-0.1 (-0.3 - 0.1)	25	25	0.1 (0 ± 0.2)	0.1 (0 - 0.3)
Skewness	20	20	-1.9 (-4.3 - -0.1)	0.9 (-1.9 - 9.3)	25	25	-0.5 (-2.9 ± 7.4)	-0.5 (-2.8 - 5.5)
Body weight								
Mean	20	20	101.3 (84.8 - 118.9)	109.9 (94.8 - 129.0)	25	25	99.6 (89.6 ± 108)	101.6 (87.7 - 116.9)
Autocorrelation (lag1)	20	20	0.8 (0.6 - 1.0)	0.8 (0.6 - 1.0)	25	25	0.6 (0.1 ± 0.9)	0.5 (0.1 - 0.8)
Standard deviation	20	20	2.8 (1.4 - 7.7)	3.7 (1.7 - 8.2)	25	25	2.8 (1.7 ± 4.2)	3.5 (2.1 - 7.4)
Slope	20	20	-0.0 (-0.1 - 0.0)	0.0 (-0.0 - 0.1)	25	25	0 (-0.1 ± 0.1)	0 (0 - 0)
Skewness	20	20	-0.3 (-2.0 - 0.9)	-0.7 (-2.0 - 0.3)	25	25	-0.1 (-4 ± 4.5)	-0.7 (-5.5 - 8.9)
Activity								
Mean	20	20	116.0 (75.1 - 177.9)	110.8 (79.4 - 154.4)	25	25	91.9 (69.1 ± 113.4)	103 (66.2 - 155.4)
Autocorrelation (lag1)	20	20	0.6 (0.2 - 1.0)	0.7 (0.3 - 0.9)	25	25	0.5 (0.1 ± 0.9)	0.4 (0.1 - 0.9)
Standard deviation	20	20	18.5 (8.9 - 39.3)	17.0 (10.1 - 33.3)	25	25	9.8 (2.9 ± 19.9)	17.7 (7.6 - 72.8)
Slope	20	20	0.0 (-0.2 - 0.3)	0.0 (-0.1 - 0.2)	25	25	0 (0 ± 0.2)	0 (-0.4 - 0.3)
Skewness	20	20	0.7 (-2.2 - 4.2)	0.6 (-1.5 - 2.9)	25	25	1.1 (-2.2 ± 4)	2.4 (-0.1 - 4.4)
Rumination activity								
Mean	20	20	105.4 (75.0 - 134.3)	99.6 (82.9 - 110.8)	25	25	98.5 (68.9 ± 154.2)	97.3 (20.7 - 155.4)
Autocorrelation (lag1)	20	20	0.3 (-0.0 - 0.9)	0.3 (0.0 - 0.6)	25	25	0.5 (0.3 ± 0.9)	0.5 (0.2 - 0.9)
Standard deviation	20	20	13.6 (9.5 - 27.6)	12.5 (10.1 - 17.5)	25	25	13 (2.9 ± 27.9)	16.3 (7.6 - 72.8)

The large overlap in average values for curve parameters indicate that the use of one single sensor to define resilience or efficiency is highly likely to be insufficient, and that a combination of curve parameters of different sensors is expected to be of more value. The combination of sensors (and curve parameters) proved its value in past research already: the detection of clinical mastitis improves in case the electrical conductivity is combined with other (sensor) data (e.g. Hogeveen *et al.*, 2010), and combining information from different sensors outperformed the automated detection of lameness compared to using a single sensor (e.g. Kamphuis *et al.*, 2013). Moreover, for a complex trait like resilience, Van Dixhoorn *et al.* (2018) concluded that the combination of static and dynamic sensor data proved the best option as indicators for resilience. Identifying which combination of curve parameters and sensors is a challenging next step in our study to use sensor information as proxy for resilience and efficiency.

Conclusion

This study used lactation FE as proxy for efficiency, and applied a point system based on four aspects to score lifetime resilience in dairy cows. Based on these definitions, there is a strong indication that the average daily milk production differs between FE and non-FE cows. Differences in curve parameters for other sensors between the two groups of efficient or resilient cows are less pronounced, and have a large overlap. This result implies that using a single sensor, or a single curve parameter, is likely to be insufficient as a proxy for resilience of efficiency. Future research should focus on studying which combination of curve parameters and sensors are most informative as proxy for these two complex traits.

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References

Borchers, M.R., and Bewley, J.M. (2015). An assessment of producer precision dairy farming technology use, prepurchase considerations, and usefulness *Journal of Dairy Science,* 98: 4198–4205.

CBS (2017). Nederlandse landbouwproductie 1950–2015. Retrieved January 9, 2019, from *https://www.cbs.nl/nl-nl/nieuws/2017/05/nederlandse-landbouwproductie-1950–2015.*

Colditz, I.G., and Hine, B.C. (2016). Resilience in farm animals: biology, management, breeding and implications for animal welfare *Animal Production Science,* 56: 1961–1983.

Egger-Danner, C.A., Fuerst, W.C. , Schwarzenbacher, H., and Fuerst-Walt, B. (2012). Hot Topic: effect of breeding strategies using genomic information on fitness and health *Journal of Dairy Science,* 95: 4600–4609.

Friggens, N.C., and De Haas, Y. (2019). Internal discussion document on definitions for resilience. Retrieved May 2 2019, from *www.gentore.eu*.

Hogeveen, H., Kamphuis, C., Steeneveld, W., and Mollenhorst, H. (2010). Sensors and clinical mastitis – the quest for the perfect alert *Sensors,* 10: 7991–8009.

Jensen, D.B., Hogeveen, H., and de Vries, A. (2016). Bayesian integration of sensor information and a multivariate dynamic linear model for prediction of dairy cow mastitis *Journal of Dairy Science,* 99: 7344–7361.

Kamphuis, C., Frank, E., Burke, J.K., Verkerk, G.A., and Jago, J.G. (2013). Applying additive logistic regression to data derived from sensors monitoring behavioral and physiological characteristics of dairy cows to detect lameness *Journal of Dairy Science,* 96: 7043–7053.

Miekley, B., Traulsen, I., and Krieter, J. (2012). Detection of mastitis and lameness in dairy cows using wavelet analysis *Livestock Science,* 148: 227–236.

Oltenacu, P.A., and Algers, B. (2012). Selection for increased production and the welfare of dairy cows: are new breeding goals needed? *Royal Swedish Academy of Sciences,* 34: 311–315.

Steeneveld, W., and Hogeveen, H. (2015). Characterization of Dutch dairy farms using sensor systems for cow management *Journal of Dairy Science,* 98: 709–717.

Van Dixhoorn, I.D.E., de Mol, R.M., van der Werf, J.T.N., van Mourik, S., and van Reenen, C.G. (2018). Indicators for resilience during the transition period in dairy cows: A case study *Journal of Dairy Science,* 101: 10271–10282.

Veerkamp, R.F. (1998). Selectin for economic efficiency of dairy cattle using information on live weight and feed intake: a review *Journal of Dairy Science,* 81: 1109–1119.

Session 7

Precision Livestock Farming Product Development, Optimisation and Testing in Field Conditions (1)

Precision Livestock Farming (PLF) technology and real-time monitoring should improve welfare in extensive systems, but does it change the duty of care and require modification of welfare guidelines for livestock keepers?

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Abstract

Improvements in animal welfare are frequently quoted for Precision Livestock Farming (PLF) technology. Extensive systems have significant and challenging welfare risks, very different from intensive systems. Predation, weather, food and water deprivation, internal and external parasites can all impact on these systems, with the animals very self-dependent. Inspection opportunities are very different. Welfare codes and supporting legal obligations are adapted to extensive and difficult environments and often have vague recommendations for inspection frequency. There are clear opportunities for PLF technologies, notably wearables, to provide more information to stockpeople, improving welfare and reducing risk. Communications from animal to stockpeople via GSM or LPWAN enables real-time monitoring (RTM) for illness, such as lameness (with IMU), for mis-mothering (with proximity), for straying away from preferred areas and/or into dangerous areas (with location technology such as GNSS), for predation/worrying from wild animals/domestic dogs (with GNSS and/or IMU). These can signify need for action or assurance for no action. However, wearables have welfare risks. Research-user experiences confirm direct welfare risks through physical damage from equipment. With infrequent inspection, small issues can become larger. There are additional animal energy demands of heavier wearables. The conservation science community note impacts of wearables for survival and reproductive success. Good design and low weight are critical issues for commercialisation. False-positive alerts and reports could involve considerable wasted time by stockpeople and new value judgements may be needed. Without RTM-based PLF, the animal could face welfare challenges or be in a poor welfare state, about which the stockperson has no knowledge, and with infrequent inspections, this state may continue or worsen. With RTM based PLF, then the stockperson should know and logically has a changed duty of care and responsibility to act upon this information.

Keywords: wearables, welfare, extensive, labour

Introduction

Extensive systems pose different challenges compared to intensive systems. Predation, weather, food and water deprivation, internal and external parasites can all impact on these systems. The animals are very self-dependent. The contrast in welfare challenges for sheep are well characterised in a major study reported by European Food Standard Agency 2014 (EFSA 2014).

Precision Livestock Farming (PLF) technology offers opportunities for extensive systems to improve welfare through improved remote surveillance, particularly RTM, and better targeted inputs of care. But extensive systems have different 'rules' with regard to animal welfare, and very different approaches in practice to the interaction between animals and stockpeople. This paper will build upon experiences gained from research, knowledge transfer and demonstration use of wearable and fixed PLF technologies in an extensive farming environment. A substantial experience has been gained with the animal welfare challenges of these systems in a series of projects aiming to consider the potential trade-

offs between welfare, labour and profitability in extensive livestock systems (Stott *et al.*, 2005, Stott *et al.*, 2012).

Human/animal interactions in extensive systems and links to welfare regulation and guidance

Inspection opportunities are very different in extensive systems than in intensive systems. Laws, welfare codes, with their own supporting legal obligations, are adapted to extensive and difficult environments and often have vague recommendations for inspection frequency.

As noted by Goddard *et al.* (2006), livestock can be either highly selected for 'survival' traits to be acceptable to a particular management system or animals which are less well adapted to the system but requiring a significant level of targeted inputs. These targeted inputs are likely to involve steps involving shepherd labour and there is potential for PLF approaches to assist in the appropriate targeting (Morgan-Davies *et al.*, 2018).

A working group for European Food Standard Agency (EFSA, 2014) reported that the quality of the human-animal interaction is composed of both the behaviour of the human, when in contact with the sheep (and hence the amount of fear that the sheep may experience), and the knowledge and skills of the stockperson in recognising animal needs and managing the sheep to achieve these. The EFSA (2014) report also recognised that the extensive nature of many systems particularly in north-west Europe and the linkages with labour inputs and inspection and human/animal interactions.

<u>The legal standpoint for shepherd input and inspection in extensive systems</u>

The legal basis can be exemplified by the UK (and Scottish) approaches through laws and welfare codes aimed to assist animal keepers to meet the law.

The UK Animal Welfare Act (2006) says:

'A person commits an offence if—

a) an act of his, or a failure of his to act, causes an animal to suffer

b) he knew, or ought reasonably to have known, that the act, or failure to act, would have that effect or be likely to

c) the suffering is unnecessary'

Following on from this, The Welfare of Farmed Animals (Scotland) Regulations 2010 requires that:

'Animals kept in husbandry systems in which their welfare depends on frequent human attention must be adequately inspected at least once a day to check that they are in a state of well-being'.

'Animals kept in systems other than husbandry systems in which their welfare depends on frequent human attention must be inspected at intervals sufficient to avoid any suffering'.

The Code of Recommendations for Sheep Welfare Code (Scotland) further says that:

'It is important for a farmer to ensure that enough time is available within the shepherd's normal work routine for the flock to be properly inspected and for any necessary remedial action to be taken'.

'The health and welfare of animals depend upon regular supervision. Shepherds should carry out inspections of the flock at intervals appropriate to the circumstances in which sheep are kept and pay particular attention to signs of injury, distress, illness or

infestation (e.g. sheep scab, fly strike, lameness and mastitis) so that these conditions can be recognised and dealt with promptly. Frequency of inspection will depend on factors which affect sheep welfare at any particular time, e.g. housing, lambing, fly strike, adverse winter weather conditions'.

Automated systems and responsibility for welfare

Within intensive farming systems for poultry, pigs and in many dairy cattle systems, automatic feeding and ventilation systems are important for the care of livestock and disruption to their efficient working can put animals at risk.

Returning to the Welfare of Farmed Animals (Scotland) Regulations 2010 it states:

'All automated or mechanical equipment essential for the health and well-being of the animals must be inspected at least once a day to check that there is no defect in it'.

'Where any defect in automated or mechanical equipment ….is discovered, it must be rectified immediately, or if that is impossible, appropriate steps must be taken to safeguard the health and well-being of the animals pending the rectification of such defects including the use of alternative methods of feeding and watering and methods of providing and maintaining a satisfactory environment'.

More efficient use of labour, improved feeding and environmental control interact and the replacement of labour by automation is one of the on-going trends within intensive systems

How might PLF technologies be a benefit in extensive systems?

There are clear opportunities for PLF technologies, notably wearables, to provide more information to stockpeople, improve welfare and reduce risk (Wathes *et el*., 2008). Communications from animal to stockpeople via GSM or LPWAN enable real-time monitoring (RTM) for illness, such as lameness (with IMU), for mis-mothering (with proximity sensors), for straying away from preferred areas and/or into dangerous areas (with location technology such as GNSS), for predation/worrying from wild animals/ domestic dogs (with GNSS and/or IMU) (Waterhouse *et al*., 2019 in press, this volume). These can signify a need for action or assurance that no action is needed.

Issues of the human/animal interaction in extensive PLF systems

The wildlife conservation science community notes impacts of wearable technologies for survival and reproductive success (Casper, 2009). Consensus-based guidelines for use of wearables in birds suggest 3% of bodyweight as an upper limit, as described by Vandenabeele *et al.* (2011) who goes on to discuss the ongoing issues around this guideline value and discusses some of the impacts above and below this threshold.

Research-user experiences confirm direct welfare risks through skin lesions from physical damage from equipment. With infrequent inspection in extensive systems, small issues can become larger before inspections and action to treat or remove the equipment. There are additional animal energy demands of wearables, ranging from negligible to significant. For animal experimental approval purposes, collars with a weight of greater than 2% of bodyweight are considered the borderline upper limit (e.g. SRUC's Animal Welfare Ethical Review Board's own working arrangements).

In terms of newly-evolving wearable technology for livestock, there are few or no standards. Within the EU, eartag design and technology has standards, but there are none for other sensors, neck or leg or tail. An issue for extensive systems is that livestock spend many days or months without inspection, so any problems in terms of abrasion and skin

lesions may not be detected early in the course of the problem. As a result, there may be greater welfare risk and challenge in these systems than intensive systems where human surveillance should be frequent. As extensive systems involve harsher environments, with poorer nutritional availability, it is arguable that the energy demand issues for wearable technology might be more sensitive to any negative impact of the wearable technology.

Furthermore, whilst many studies focus on recording, analysing and interpreting patterns of behaviour using wearable technology, these studies typically focus on the production objectives and seeking to confirm how well the equipment and software can gather useful information. By contrast, there has been little published information on the impact, or lack of, on animal performance and welfare measures that result from wearing technology in livestock. One early study, by Hulbert *et al.* (1998), sought to determine whether wearing collars close to the 2% of bodyweight impacted upon patterns of sheep behaviour. Daily time budgets and animal location movements of collared and uncollared sheep were compared and theoretical energy requirements of grazing sheep with an added 863 g GPS neck collar (1.7% bodyweight) were calculated, with extra energy requirements less than 1%.

Good design and robust testing, including in challenging conditions, should be an expectation of new products. However, the precision livestock science community has spent relatively little effort considering the variables that might influence the welfare risks of wearable technologies; namely weight, location (neck, body, ankle), duration and physical attachments and potential abrasion characteristics. Furthermore, the environmental challenges faced by extensive animals, such as rain, snow, drought, dust, combined with nutritional, or parasite challenges may put extensive animals under greater, or different risks to those kept in more intensive systems. Fundamentally, this equipment is likely to be on animals for considerable periods without human inspection.

New PLF approaches for extensive sheep and cattle systems

Wathes *et al.* (2008) questioned the focus in PLF modified systems and whether it would be towards efficiency, profitability, animal health or welfare and queried whether optimising the process to meet one overall target can have implications for another, e.g. the farmer's income *vs*. animal welfare.

New precision farming technology that provides improved decision support should provide extensive livestock farmers with better information to target the input of care identified by Goddard *et al.* (2006) to maintain both welfare and production. Ideally, there would be an improvement in both.

However, there is a potential problem. To finance the new technology, there needs to be either or both an increase in production or reduction in costs. For extensive systems, labour is a major proportion of costs. There is a case to be made that increased use of PLF, in this case remote surveillance, needs to be financed at least in part by reduced labour. In intensive systems, with regular inspections then this replacement is easy to envisage and creates a few potential dilemmas. However, in current extensive systems, the expectation and reality is that inspection and human/animal interactions are already infrequent. Without surveillance, knowledge of any animals 'in trouble' cannot be known by stockpersons and the system falls back upon the self-reliance of the breeds and robustness of the system. Much of current health care involves prevention not cure in current systems.

However, with RTM surveillance data from sensors direct to smartphones, entirely new types and levels of information will be provided to extensive livestock farmers. Does this

new information bring with it new responsibilities, in addition to new opportunities? If the farmer, and the animals, also become reliant upon the new surveillance approach, is this responsibility comparable with an intensive farmer with an alarm to provide alarms to signal that the ventilation system has broken, and not repairing the ventilation system when it breaks? Will laws, guidelines and codes of welfare need to change to take into account the role of RTM and wearable technology? As a further note of an emerging issue, could the 'digital signature' of a PLF decision support system, provide 'digital fingerprints' of the important 'Failure to Act' element seen in the UK Animal Welfare Act (2006)?

Table 1 provides a few realistic examples of the current animal welfare issues for an extensive livestock farmer and the new information flow which may occur with adoption of an RTM system. As animal welfare is very much about the welfare of the individual, then each of the cases in the table should lead to identical, and direct, rapid action. A question to pose with the low value animals within typical extensive systems is whether the actions would be equal in reality. The table also highlights the issues with false-positive information, easily checked in an intensive system, but potentially time-consuming to check in extensive systems.

Finally, as noted by Goddard *et al.* (2006), members of the general public are believed to highly value natural aspects of animal production which are often found in extensive systems. Does intervention with automated systems of surveillance and management change this belief?

Table 1. Some ethical challenges of traditional and PLF-surveillance systems

Hierarchies of acute welfare issues – traditional approach
Shepherd finds horned ewe caught in fence
Member of public reports a sheep caught in fence at known location
Member of public reports a sheep but cannot be sure where it was
Phone message saying sheep caught in fence – no location mentioned
Hierarchies of acute welfare issues – PLF approach
Smartphone says ewe is immobile and prostrate near fenceline
Smartphone says ewe is immobile and prostrate high on hill – no fences
Smartphone says 50% probability that a ewe is immobile and at risk, high on hill
Examples of long-term welfare issues and information flow
Hillwalker tells shepherd that 'a few sheep on hill were lame' (2 hours walk away)
Alert on smartphone - 1 ewe is lame in field near farmhouse
Alert on smartphone – 1 ewe lame high on hill (2 hours walk away)
Alert on smartphone – 5 lame ewes high on hill (2 hours away)
Alert on smartphone – probability 50% that 1 ewe high on hill is lame

Conclusions

The differences between intensive and extensive systems lead to different issues associated in the relationship between welfare, improved capacity for remote surveillance of livestock and the interactions and interventions of stockpeople with their livestock. New PLF technology offers the potential to improve welfare in extensively farmed livestock through better targeting of care and inputs. Increased use of surveillance systems also offers the potential to identify animals in short and long term difficulties. The costs of

new PLF needs to be financed by improved outputs or reduced inputs, or both. However, there is no certainty about whether labour costs will be reduced or increased by the new information flow that RTM data flow may provide. False-positive alerts and reports could involve considerable wasted time by stockpeople and new value judgements may be needed in terms of when action is taken as a result of RTM information.

Without RTM-based PLF, the animal could face welfare challenges or be in a poor welfare state, but the stockperson has no knowledge of this status, and with infrequent inspections, this state may continue or worsen. With RTM-based PLF, then the stockperson should know and logically has a changed duty of care and responsibility to act upon this information.

Wearable technology in livestock is still in its infancy, but both scientific practices and commercialisation processes need good practices to ensure there are no negative impacts of wearing the technology. Policy-makers involved in framing animal welfare guidelines and legislation need to recognise that whilst wearable technology, especially when involving real-time, changes the relationship between the animals and those responsible for them. Technology may provide opportunities to improve welfare, but it also, by providing more information, changes the duty of care to the animals. It is arguable that these changes will be most profound in extensive systems, where current inspection routines are minimal.

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References

Casper, R.M. (2009). Guidelines for the instrumentation of wild birds and mammals. *Animal Behaviour,* 78(6): 1477–1483.

EFSA (2014). European Food Standards Authority Panel on Animal Health and Welfare *Scientific opinion on the welfare risks related to the farming of sheep for wool, meat and milk production*. EFSA Journal, 12(12): 3933.

Goddard, P., Waterhouse, T., Dwyer, C. and Stott, A. (2006). The perception of the welfare of sheep in extensive systems. *Small Ruminant Research*, 62(3): 215–225.

Hulbert, I.A.R., Wyllie, J.T.B., Waterhouse, A., French, J. and McNulty, D. (1998). A note on the circadian rhythm and feeding behaviour of sheep fitted with a lightweight GPS collar. *Applied Animal Behaviour Science,* 60(4): 359–364.

Morgan-Davies, C., Lambe, N., Wishart, H., Waterhouse, A., Kenyon, F., McBean, D. and McCracken, D. (2018). Impacts of using a precision livestock system targeted approach in mountain sheep flocks. *Livestock Science,* 208: 67–76.

Stott, A.W., Milne, C.E., Goddard, P.J. and Waterhouse, A. (2005). Projected effect of alternative management strategies on profit and animal welfare in extensive sheep production systems in Great Britain. *Livestock Production Science,* 97(2-3): 161–171.

Stott, A.W., Vosough Ahmadi, B., Dwyer, C.M., Kupiec, B., Morgan-Davies, C., Milne, C.E., Ringrose, S., Phillips, K., and Waterhouse, A. (2012). Interactions between profit and welfare on extensive sheep farms. *Animal Welfare*, 21: 57–64.

Vandenabeele, S.P., Shepard, E.L., Grogan, A. and Wilson, R.P. (2011). When three per cent may not be three per cent; device-equipped seabirds experience variable flight constraints. *Marine Biology*, 159(1): 1–14.

Waterhouse, A., Holland, J.P., McLaren, A., Arthur, R., Duthie, C-A, Kodam, S. and Wishart, H. (2019). Opportunities and challenges for real-time management (RTM) in extensive livestock systems, This volume.

Waterhouse, A. (1996). Animal welfare and sustainability of production under extensive conditions—A european perspective. *Applied Animal Behaviour Science,* 49(1): 29–40.

Wathes, C.M., Kristenson, H.H., Aerts, J-H., and Berckmans, D. (2008). Is precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall? *Computers and Electronics in Agriculture,* 64(1): 2–10.

Predicting grass growth on farm, utilisation of the MoSt Grass Growth model

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Abstract

The Moorepark St Gilles Grass Growth (MoSt GG) model was developed to predict grass growth, grass nitrogen (N) content and N leaching on a daily basis depending on soil type, fertilisation and grazing management. The inputs required are at the paddock level and are soil type (% sand, % clay), percentage of organic matter, the weather historical and forecast (daily rainfall, solar radiation and temperature), the N fertilisation (type and amount), and the defoliation management (day of grazing/cutting, number of animals on the paddock, post grazing/cutting height). All the information concerning N fertilisation and defoliation management are present in a decision support tool called PastureBase Ireland (PBI). The model was evaluated against data from PBI (2013–2018) on a number of farms. The model showed good accuracy and was able to take into account variation between the different years and grazing/fertilisation management. Since January 2018, the MoSt GG model was used weekly to predict grass growth for three farms. The model used historical management (from PBI) and weather data, as well as weather forecast provided by Met Eireann, to predict the grass growth of the following week. This live evaluation highlighted a number of strengths and weaknesses of the model during the challenging year that was 2018. The prediction of grass growth helped the farm managers' weekly management decisions. Since January 2019, the model is being used on 40 farms. Grass growth is communicated to farmer and farm manager through WhatsApp at least once a week. The next step will be the full integration into PBI.

Keywords: grass growth, model, predictions, on-farm

Introduction

Each additional kilogram of grass dry matter (DM) utilised on farm increases farm benefit (Hanrahan *et al.*, 2017). In Ireland, an increase of one tonne of grass DM/ha eaten will increase profit by €105/ha on beef farms and €181/ha on dairy farms. PastureBase Ireland (PBI; (Hanrahan *et al.*, 2017)) is a grassland management tool for farmers. It helps farmers to manage the grass on their farm, identify grass supply surpluses or deficits and to take appropriate action. Several grassland management tools are available such as the spring and autumn planner and the grass wedge. However, currently within PBI, farmers can only make decisions based on historical information. Incorporating a means of predicting grass growth based on management and weather forecast would be very useful in PBI.

The Moorepark St-Gilles Grass Growth (MoSt GG; (Ruelle *et al.*, 2018)) model was developed through a collaboration between Teagasc and INRA, and can predict grass growth, grass nitrogen (N) content and N leaching. The main objective in developing the MoSt GG model was to have a model which can be useful from a research and from a farmer's point of view. The inputs have been kept as simple as possible to ensure its easy utilisation.

This paper will describe the results of the different evaluations and the acceptance by farmers and the future work.

Material and methods

The MoSt GG (Ruelle *et al.*, 2018) is a dynamic model developed in C++ describing the grass growth and the N fluxes of a paddock at a 2 m^2 level. The model is run with a daily

time step simulating soil N mineralisation/immobilisation and water fluxes, grass growth, N uptake and grass N content. The model is driven by daily potential growth depending on the radiation and the total green biomass. To calculate the actual daily growth, this potential growth is then multiplied to environmental parameters (temperature, water in the soil and radiation) and a parameter describing the availability of the soil mineral N compared to the N demand associated with the potential grass growth. The availability of the N in the soil depends on the mineral N in the soil, the proportion of the N that can be used by the plant (depending on the time of the year and the heading date) and the N demand to grow one kg of biomass dry matter (depending on the N dilution curve and the actual biomass over 4 cm – (Gastal and Lemaire, 2002)).

Evaluation years 2013-2018

The MoSt GG model was evaluated using experimental data for 2013-2018 from three Teagasc experimental farms - Ballyhaise, Clonakilty and Curtins. Corresponding weather data were extracted from a weather station nearby and information about N fertiliser application, grazing and cutting events, as well as biomass and growth (for each herbage mass estimation entered by the farm manager) was imported from PBI. Data from 2017 was missing for Curtins' farm due to changes to paddock sizes and reseeding in the middle of the year; and data was missing for a Clonakilty farm for 2018 because no weather data were available. The soil type used for the simulations was a sandy loam (38% sand, 27% clay) for Curtins' farm and a loam (55% sand, 15% clay) for the Clonakilty farm according to information given by the farm manager. For Ballyhaise farm, more information was available and the soil type ranged from a peaty clay (15% sand, 70% clay) to a loam (38% sand, 27% clay). The organic matter content of all paddocks was available from soil test conducted prior to or during the evaluation years.

For each year for each paddock on each farm, a simulation was run using the soil type (percentage of sand clay and OM), weather, fertiliser application (amount and date), cutting event (date and post cutting height), and grazing event (date, number of animals and post grazing height) as input data. On the date of an herbage mass estimation, the biomass in the model was corrected using the herbage mass estimated by the farm manager.

The grass growth calculated in PBI based on the herbage mass estimation by the farmer was compared to the growth for the exact same period predicted by the MoSt GG model at the paddock level.

The RMSE is calculated as (Bibby and Toutenburg, 1977)

$$RMSE = \sqrt{\frac{\sum(A-P)^2}{n}}$$

with A the PBI growth and P the MoSt growth for a specific day.

The evaluation was undertaken at the paddock year, farm year and farm level.

Pilot program 2018-2019

In 2018, the model was live tested on three farms, two Teagasc farms (Curtins, Co. Cork and Ballyhaise, Co. Cavan) and one commercial farm in Mitchelstown (Co. Cork). The weather forecast for each location was provided Met Éireann (The Irish Meteorological Service). Apart from the weather, the other inputs in terms of N fertiliser application, grazing and cutting events were extracted weekly from PBI for each farm.

Since January 2019, the model is being used to predict grass growth on 40 farms across Ireland. The farms selected completed more than 30 farm covers (herbage mass estimation)

and recorded N fertiliser application in PBI in 2018. The farms are representative of soil type and geographic variability of Ireland. Historical and forecast weather data is provided for each individual farm by Met Éireann. Information about N fertiliser and grazing and cutting events are imported from PBI weekly. The soil type of each paddock on each farm was determined using the Irish Soil Map of Ireland. All the soil types available within 5 km^2 of the farm and their characteristics in terms of soil depth, horizon, sand and clay percentage, and organic matter content were extracted from the soil data shapefile. Using the 2018 weather specific to each farm, simulations were run for each paddock using each soil type available for the farm, as well as the actual N fertilisation, grazing and cutting events conducted on each paddock. The soil type for each paddock resulting in the lowest error was linked to the paddock for the 2019 simulations. This optimisation will be re-conducted every three to six months with the new data available.

Result and discussion

Evaluation

The results of the evaluation of the model are presented at the paddock (Table 1) and at the farm (Table 2) level. Overall the model showed a similar accuracy across farms. The accuracy at the paddock level with RMSE of between 27 - 32 kg DM/ha day is quite poor, however, the accuracy at the farm level of between 11 - 18 kg DM/ha/day is quite promising. When looking at those results, it is important to remember that the data entered into PBI corresponds to visual assessment of the herbage mass on a paddock completed by the farmer and not actual measurement, which could explain some of the large errors at the paddock level. Some of the errors in the model could also be explained by the absence of detailed information on soil type which results in poor simulations.

Table 1. Evaluation of the predicted growth (kg DM/ha/day) on three Teagasc farms at the paddock level. The growth calculated in PBI for each paddock is compared to its simulated equivalent by the MoSt GG

Farm	Ballyhaise			Curtins			Clonakilty		
	PBI	MoSt	RMSE	PBI	MoSt	RMSE	PBI	MoSt	RMSE
2013	50.7	49.0	27.3	46.6	46.9	28.2	45.5	45.3	27.6
2014	60.0	52.9	31.7	57.0	56.6	31.1	47.4	45.2	26.9
2015	46.6	48.6	22.8	53.5	51.9	28.2	53.6	51.2	27.6
2016	47.9	48.2	24.3	52.1	48.6	28.2	49.6	48.5	30.8
2017	49.7	47.7	24.5	NA	NA	NA	49.6	51.7	28.1
2018	44.1	45.0	28.7	37.3	36.1	27.3	NA	NA	NA
All years	49.7	48.4	26.8	45.8	44.6	28.2	49.1	48.4	28.3

Table 2. Evaluation of the predicted growth (kg DM/ha/day) on three Teagasc farms at the farm level. Each average farm growth calculated based on garbage mass estimation in PBI for each farm is compared to its simulated equivalent by the MoSt GG

Farm	Ballyhaise			Curtins			Clonakilty		
	PBI	MoSt	RMSE	PBI	MoSt	RMSE	PBI	MoSt	RMSE
2013	50.7	49.0	12.7	46.6	46.9	16.8	45.5	45.3	15.4
2014	60.0	52.9	17.2	57.0	56.6	15.3	47.4	45.2	14.8
2015	46.6	48.6	11.5	53.5	51.9	13.6	53.6	51.2	13.2
2016	47.9	48.2	15.3	52.1	48.6	15.7	49.6	48.5	17.9
2017	49.7	47.7	14.2	NA	NA	NA	49.6	51.7	14.3
2018	44.1	45.0	17.2	37.3	36.1	16.3	NA	NA	NA
All years	**49.7**	**48.4**	**6.9**	**45.8**	**44.6**	**9.4**	**49.1**	**48.4**	**7.6**
Spring	23.4	25.4	13.0	32.4	31.4	10.2	31.4	32.2	9.9
Summer	74.1	76.0	17.0	69.1	73.6	18.6	77.1	80.1	19.3
Autumn	57.9	51.1	15.3	51.7	48.4	15.4	52.4	51.0	15.0

The model was able to adapt to the different years and different soil types. The graph of the best and worst years in term of RMSE is presented in Figure 1.

Feedback of the start of the pilot program

In 2018, the grass growth prediction was sent each Monday to the farm manager. The model adapted to the different growth patterns on the farms, as well as to the extreme conditions of 2018 with a very wet and cold spring and a very dry summer. The feedback from the farm managers was very positive, and the farmers consider the predictions very useful aids to decision making in challenging times. Differences between predictions using forecast and actual weather occurred. The solar radiation predictions have been identified as the biggest factor impacting the difference between simulations with historical or forecast weather. Solar radiation is difficult to predict because it is affected by cloud cover.

Since February 2019, the weekly grass growth has been communicated to farmers involved in the pilot study in the form of a map sent to the farmers on a Monday (Figure 2).

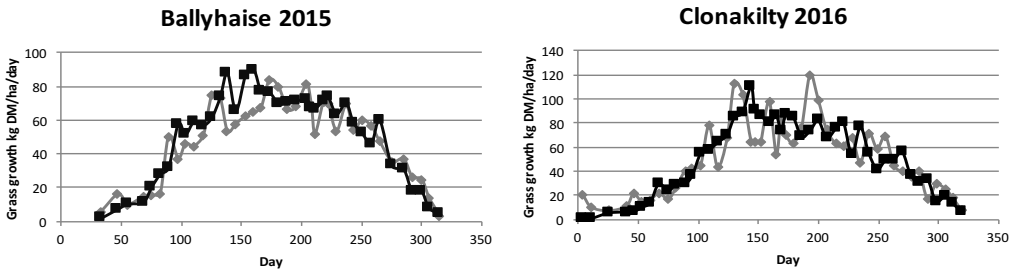

Figure 1. Representation of the best (Ballyhaise 2015) and the worst (Clonakilty 2016) predictions by the model at the farm level. MoSt GG model prediction is the black line, and the growth predicted in PBI from herbage mass estimation is the grey line

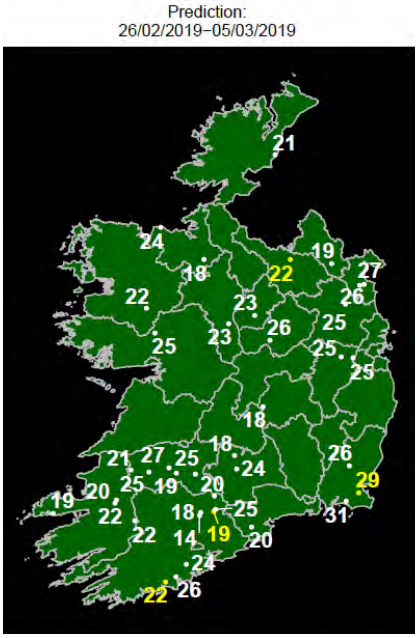

Figure 2. Grass growth prediction sent to farmers in the pilot study for the period of 26 February to 5 March 2019. Numbers in white correspond to commercial farms, numbers in yellow correspond to experimental Teagasc research farms

Future of the MoSt model: Integration into PBI

If the pilot study is successful, and the accuracy of the model is sufficient across the different farms, the model will be into PBI.

Future of the MoSt model: research

The model has already been used to answer the key research question such as the impact of climate change on grass growth in Ireland (Ruelle *et al.*, 2018). Currently, the model is used to investigate the best timing of fertiliser application in early spring depending on weather and soil type. In the future, it is planned to use the model to evaluate the impact of different management on the environment depending on the weather condition. At the moment, only N is simulated but the addition of other nutrients will be investigated to improve the quality of the prediction in terms of performance as well as environmental impact.

Conclusion

The MoSt grass growth model is a mechanistic model developed for both research and farm use. The initial on-farm testing (2018) indicates that the model is capable of adapting to differences in farms and in weather conditions. The larger pilot study currently on-going will provide a true indication of the MoSt GG model's ability to provide useful grass growth prediction across soil types, regions and management conditions.

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References

Bibby, J., Toutenburg, H. (1977). *Prediction and improved estimation in linear models*, Wiley New York.

Gastal, F., Lemaire, G. (2002). "N uptake and distribution in crops: an agronomical and ecophysiological perspective." *J. Exp. Bot.*, 53(370): 789–799.

Hanrahan, L., Geoghegan, A., O'Donovan, M., Griffith, V., Ruelle, E., Wallace, M., Shalloo, L. (2017). "PastureBase Ireland: A grassland decision support system and national database." *Comput. Electron. Agric.*, 136: 193–201.

Ruelle, E., Delaby, L., Hennessy, D. (2018). "Impact of climate change on grass growth at two sites in Ireland." *Sustainable meat and milk production from grasslands, Proceedings of the 27th General Meeting of the European Grassland Federation* Cork, Ireland, 538–539.

Ruelle, E., Hennessy, D., Delaby, L. (2018). "Development of the Moorepark St Gilles grass growth model (MoSt GG model): a predictive model for grass growth for pasture based systems." *Eur. J. Agro.*, 99: 80–91.

Can a new electronic warning system prevent collisions between vehicles and semi-domestic reindeer?

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Abstract

Collisions between vehicles and animals have increased in Norway and Europe over the last 40 years, causing economical losses as well as poor welfare for animals and people. In Norway 2 m high deer fences have been put up to prevent killings of semi-domestic reindeer at some limited road- and railway distances. However, these are very expensive and animal passages are needed. As a supplementary measure, an electronic system, aimed at warning the driver if reindeer are close to the road, was tested along the E6 main road at Saltfjellet, Norway, during March - April 2018. 235 female reindeer were equipped with radio transmitter collars (805.15.4 866 MHz). The animals were grazing in a collision exposed area at Saltfjellet. A total of 41 receivers were mounted on road sticks alongside the 4.5 km test distance. When a reindeer with transmitter was within 50 - 100 m proximity to a road stick, the receiver started blinking red. Saltfjellet reindeer herding district lost 15 reindeer in the test area from December 2017 until test start in February 2018. No reindeer were hit by cars during the test period. Nevertheless, 25% of the receivers became defective after a while, most possibly due to battery shortage. A new generation of transmitters and receivers was tested at Saltfjellet during December 2018 - April 2019. Preliminary results from this extended test are presented. We evaluate the electronic warning system as promising. However, improvements are needed in order to achieve optimal receiver and transmitter reliability in function.

Key-words: animal-vehicle collisions, electronic devices, preventive measures, real-time detection

Introduction

Collisions between vehicles and animals have increased in Norway and Europe over the last 40 years (Hughes *et al.,* 1996; Knapp *et al.,* 2004; Rolandsen *et al.,* 2015). Such collisions result in serious economical losses, but also represent a considerable welfare issue for animals and people. In Norway, more than 3,000 reindeer have been killed by the railway in the last 10 years (Rolandsen *et al.,* 2017; Stanimirov *et al.,* 2018). In 2017 alone, 514 semi-domestic reindeer were killed at 'Nordlandsbanen', a railway track in mid- and Northern Norway which is 729 km in length, costing about €500,000 in compensations. Because reindeer is a highly gregarious species, as many as 80 animals have been killed by the train in the same collision event.

Many mitigation measures have been tested. Mitigation measures might be divided into four different categories: 1) physical barriers; 2) measures that reduce the local density of animals; 3) measures that scare the animals, and 4); measures that warn the driver, of which the two latter categories include different types of electronic devices. In Norway, 2 m high deer fences have been established at some limited road- and railway distances. This is the most effective measure to prevent collisions with animals, however, fences are very expensive as well as fragmenting the pasture areas, thus animal passages are needed (Rolandsen *et al.,* 2017). In addition, the fences affect other mammals' natural movement in the terrain. Electronic devices that scare the animals are most often based on light

and sound signals, however, the effect on semi-domestic reindeer, and particularly in the dark, is not known (Wagner *et al.,* 2019, in press). Furthermore, animals usually habituate quite fast to such measures (Bomford & O'Brien 1990). Mitigation measures that warn the drivers, based on different animal detection systems, are more promising. The problem with unspecified detection systems (IR-cameras, motion sensors, beam-brake systems etc.) is that they trigger many error signals (false positives), because the detection system is not specific enough (Huijser *et al.,* 2005). Detection of GPS-instrumented semi-domestic reindeer is another possibility (GPS connected to GEOfencing or other virtual fencing), but the GEOfencing technology is still premature and these kind of systems are too expensive today. A cheaper technology for real time detection of instrumented semi-domestic reindeer might be the solution. Nevertheless, transmitters should weigh little, should not accumulate ice on the collars, have large battery capacity (at least more than one year) and be low-cost. The receivers should warn the driver only when animals are present and have sufficient battery capacity (at least four months during the darkest time of year). Both transmitters and receivers should function, over time, in an Arctic winter climate.

The aim of the experiment was to develop and test a new electronic device that warns the driver when animals are close to roads. The main goal is to reduce the number of collisions between vehicles and semi-domestic reindeer.

Materials and methods

Animals, location and electronics

235 semi-domestic female reindeer from two herds were equipped with radio transmitters (805.15.4866 MHz) integrated into their collars. The animals were grazing together with the rest of their flock in an area at Saltfjellet located close to the Arctic Circle (66^0 N). The area was prone to vehicle-animal collisions. The receivers were connected to led lights and integrated in a light globe that started blinking red when the receiver was activated. A total of 41 receivers were mounted on road sticks alongside the 4.5 km test distance. When a reindeer with transmitter was within 50 - 100 m proximity to a road stick, the receiver flashlight (RF) was activated.

The technology was developed and designed at the Umeå University Embedded Systems Lab. Battery capacity and casings were tested by putting both receivers and senders in a freezer for nearly one year. Estimated battery life of the transmitters was five years and production costs were about €10. The electronic warning system was tested initially on sheep at a home pasture close to NIBIO Tjøtta Research Station ($65\ ^0$ N) and at a small semi-domestic flock of reindeer in corrals at Tverrvatnet ($66\ ^0$ N), close to Saltfjellet.

Data recording

A supervisor from Mesta (contractor of operations and maintenance for the Norwegian Public Roads Administration, NPRA) checked the receivers once a week by driving slowly in a car with a transmitter passing all the RFs. Any receiver that was not activated by the transmitter during the test period was registered. The number of semi-domestic reindeer with and without transmitters killed by cars within the test distance before and during the 2 months test period (February 22th – April 26th 2018) was recorded.

At the present time a new generation of transmitters and receivers (Figure 1) were tested at the same location (December 2018 - April 2019). Another 200 semi-domestic reindeer were equipped with radio collars. Data on receiver reliability in operation is checked every week by Mesta. Additionally, five of the receivers are connected to GSM. Reports from these are sent to a web site every hour, if activated, logging each transmitter (by ID-number) that has trigged the receiver. Furthermore, on 13 February 2019 a random sample test of

the reliability in operation of 120 transmitters was conducted. At the same date the NPRA established speed indicators outside and within the test distance. The number of semi-domestic reindeer with and without radio collars killed by vehicles in the test area will be collected throughout the test period.

Figure 1. The flashlight receiver and the transmitter integrated in a reindeer collar (photo: Johannes Karlsson)

Results and discussion

Saltfjellet reindeer herding district lost 15 reindeer in the test area from December 2017 until test start. No reindeer (with or without transmitters) were hit by car during the test period. Nevertheless, by end of the study, 25% of the receivers stopped working, most possibly due to battery shortage. Preliminary results from Saltfjellet 2019 show that many semi-domestic reindeer are killed by traffic this winter, but none with transmitters so far within the test area. By mid-February 2019, three out of 39 RFs had stopped working (8%) and the random check of radio transmitters showed that, for unknown reasons, 35% of the transmitters were defect.

There has been continuous development of casings and upgrading of the technology during the research period. The latest generation of RFs seem to work better than the initial ones, most probably due to small software adjustments. Less energy demanding procedures for activating the receivers have resulted in longer battery life. The random sample test of radio transmitters in February 2019, however, showed rather disappointing results. Nevertheless, since reindeer flock together it is not necessary that all individuals wear radio collars. Indeed, results from 2018 show that no animals, neither with nor without radio collars, were killed in collisions within the test area. Results 2019 will show if this is due to the drivers' behaviour, i.e. if the car drivers slow down when warned by the flashlights. Overall, we evaluate the electronic warning system as promising. Further improvements are needed, in order to achieve optimal receiver and transmitter reliability in function.

Although deer fences are the most effective measure in preventing animal-vehicle collisions, these are very expensive and cannot be put up along complete road or railway distances (Rolandsen *et al.,* 2017). The new electronic warning system is meant to be a supplement to deer fences, and might cover more of the collision-prone 'hotspots'. It will probably be sufficient to run this warning system during winter, when the probability for collisions is at the highest due to large amounts of snow and the polar night (Rolandsen *et al.,* 2015; Rolandsen *et al.,* 2017; Stanimirov *et al.,* 2018). Another advantage over fences is that this new electronic system is not fragmenting the reindeer pasture areas or disturbing other animal species.

To date, there is no particular technological solution that can solve the problem of collisions between train and domestic reindeer along the Norwegian railways (Wagner *et al.,* 2019, in press), especially not in a harsh Arctic climate. It is accepted knowledge that reducing

speed is the most effective way to reduce animal-vehicle collisions (Kistler, 1998; Romer & Mosler-Berger, 2003; Mosler-Berger & Romer, 2003) and this is also the method most frequently requested by reindeer herders (Rolandsen *et al.,* 2017). Wagner *et al.,* (2019, in press) therefore, recommend mitigation measures that involve real-time warning systems to the train drivers for effective speed control with appropriate breaking distances. These systems must consist of an animal detection system and a communication system that alerts the train driver. We consider adaptations of our new electronic warning system for the Norwegian railways. By supplying all receivers with sim-cards, the train drivers (and also the reindeer herders) can receive an SMS when an animals has activated a receiver. Another potential for extended use of the reindeer transmitters is animal identification. Since each tag has a unique ID, this could be matched with owner, age, sex and other animal-based information. In the future, we think it might be possible to scan a whole reindeer herd wearing transmitters by using a drone carrying a receiver.

Conclusions

Results from the tests at Saltfjellet show that the new electronic warning system has a promising potential. Improvements are still needed in order to achieve optimal receiver and transmitter reliability in function. The electronic warning system may be used both for roads and railways in the future.

Acknowledgements

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References

Bomford, M., and O'Brien, P.H. (1990). Sonic deterrents in animal damage control: A review of device tests and effectiveness. *Wildlife Society Bulletin*, 18: 411–422.

Hughes, W.E., Saremi, A.R. and Paniati, J.F. (1996). Vehicle-animal crashes: an increasing safety problem. *Institute of Transportation Engineers Journal,* 66: 24–28.

Huijser, M.P., McGowen, P.T., Camel, W., Hardy, A., Wright, P. and Clevenger, A.P. (2005). *Animal vehicle crash mitigation using advanced technology. Phase I: review, design and implementation.* Technical Report by the Western Transportation Institute, Montana State University, USA.

Kistler, R. (1998). *Wissenschaftliche Begleitung der Wildwarnanlagen Calstrom WWA-12-S. Juli 1995-November 1997. Schlussbericht.* Infodienst Wildbiologie and Ökologie. Zürich, Switzerland.

Knapp, K., Yi, X., Oakasa, T., Thimm, W., Hudson, E. and Rathmann, C. (2004). *Deer-vehicle crash countermeasure toolbox: a decision and choice resource. Final report.* Report Number DVCIC – 02. Midwest Regional University Transportation Center. Deer-Vehicle Crash Information Clearinghouse. University of Wisconsin-Madison. Madison, WI, USA.

Mosler-Berger, C. and Romer, J. (2003). Wildwarnsystem CALSTROM. *Wildbiologie* 3: 1–12.

Rolandsen, C.M., Solberg, E.J., Van Moorter, B. and Strand, O. (2015). *Dyrepåkjørsler på jernbanen i Norge 1991–2014.* NINA Rapport 1145.

Rolandsen, C.M., Langeland, K., Tømmervik, H., Hesjedal, A., Kjørstad, M. Van Moorter, B., Danielsen, I.E., Tveraa, T. and Solberg, E.J. (2017). *Tamreinpåkjørsler på Nordlandsbanen.* NINA Rapport 1326.

Romer, J. and Mosler-Berger, C. (2003). Preventing wildlife-vehicle accidents. The animal detection system CALSTROM. In: *Proc. Infra Eco Network Europe (IENE) Conference* Brussels, Belgium.

Stanimirov, M., Mahaboob, S. and Staurem, E. (2018). *Handlingsplan for å redusere antall dyr påkjørt med tog 2018–2021*. Bane NOR, 2.ed., 1–33.

ChickenBoy: a farmer assistance system for better animal welfare, health and farm productivity

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Abstract

The ChickenBoy is a robotic farmer assistance system. It is the worldwide first ceiling suspended robot that aims to assess aspects of animal welfare and help farmers increase farm productivity. At the current stage, the ChickenBoy measures climatic conditions (temperature, relative humidity, CO_2 and air speed), examines excrements using artificial intelligence, finds dead birds and defective nipple drinkers and identifies wet spots in the litter. Farmers access the robot via a cloud-based user interface or subscribe to one of the 15 available alerts that sends messages directly onto the farmer's phones. We have created a full-scale economic model of farm performance to assess the impact of the ChickenBoy on farm productivity and to convince farmers that higher welfare can mean higher profits. In this contribution, we will present the current state of the development with results from European farms.

Keywords: broiler real-time surveillance robot, dead birds, defective nipple drinkers, wet spot recognition, climate, faeces analysis, farmer alert system

Introduction

The global livestock sector has profoundly changed in the course of recent decades in response to globalisation and growing demand for animal-source foods, driven by population growth and increasing wealth in much of the developing world (Robinson *et al.*, 2011). The production of farm animals delivering milk, meat and eggs has grown in the last 50 years by a factor of four. World meat production rose from about 200 million tons in 1995 to about 280 million tonnes today and will continue to grow presumably to an estimate (without fish) of about 350 million tons in 2030 (FAO). Highest increases are expected in developing countries while meat production in developed countries will increase only slightly or will stagnate. In total approximately 60–70 billion animals are raised, transported and slaughtered every year (The Economist 2011; Anonymus 2019).

This enormous increase of production was only possible by a revolution in agriculture and livestock production since the 1970's that can be characterised by the terms intensification and specialisation. Significant breeding progress was associated with the development of specialised farms with modern intensive indoor production, where the animals are kept in confined houses at high stocking rates all year round, in order to make best use of their selected genetic qualities that enable them under appropriate housing, feeding, hygiene, management and veterinary control to reach high growth rates and high feed efficiencies in the shortest possible time. In consequence, poultry production increased dramatically. Farms raising 30–40,000 broiler birds per barn became common in Europe and many other parts in the world and prices of broiler meat dropped. For the first time in human history, Europeans do not need to worry about sufficient animal-source food supply (Hartung, 2013).

Soon two serious problems appeared. First, the consumer, increasingly disconnected from the fast development of modern farming, is increasingly concerned about the welfare of the animals in these 'animal factories' where the birds are kept solely under commercial

conditions, not regarding their species-specific nature (Harrison 1964). Consequently, resistance has grown in recent years to 'industrial' farming. Second, farmers and farm workers have problems to survey health and welfare of broilers in these large herds in an economically justifiable timeframe. In front of this conflicting background, a farmer assistance system for broilers, called ChickenBoy, was developed combining mechanical robustness with modern sensors and advanced digitalization (4.0) technology.

This paper will present the latest state of the development and gives examples of measurements in commercial farms.

Material and methods: Description of the ChickenBoy

Figure 1 gives a view of the ChickenBoy system. The robot consists of two major parts connected with a telescopic rod that can automatically move up and down according to the measuring programme. The system runs on rails that are fixed to the ceiling of the barn. Depending of the size of the barn, rails are mounted to the ceiling meandering through the whole barn. The cameras can cover about 90% of the floor space. One battery charge is sufficient for about one km driving distance of the robot. It returns back automatically to the charging station and reloads automatically. Loading time up to 4 h. The robot can run in different speeds between 10–30 cm / s.

Figure 1. View of a ChickenBoy robot showing the rails, driving engines, upper platform with electric equipment and battery, the retractable telescopic rod and the sensor platform with sensors and the lateral camera set

Four wheels are running on the rails, two are equipped with small cylindrical electric engines which drive the robot forwards. The engines are powered by a battery located in the head section of the robot. In the lower section, the sensors and cameras are installed. For the measurement of air temperature, relative humidity of the air, carbon dioxide

(CO_2) and air speed animal house proven sensors are used. Both camera sets consist of a visible and an infrared camera, with which continuous 'normal' and thermal images can be recorded. One camera set is mounted sidewise of the sensor platform directed to the nipple drinker lines in order to recognise too fast dripping nipples. The other camera set is fixed to the bottom side of the platform and traces birds with very low body temperature (dead birds) and wet spots in the litter. An additional feature is the examination of the faeces of the birds using artificial intelligence in order to detect early signs of diarrhoea. The sensor platform runs usually 40–50 cm above the heads of the animals.

The data are transmitted to a database where they are stored in a protected, cloud-based system. The farmer has access to the robot and the data via a user interface. He can receive e.g. hourly via PC or smart phone measuring results mapped across the barn floor. This enables him to take early action in case of animal disorders or technical failures. The data mapping leads him directly e.g. to a broken drinker or an animal which needs help or a dead bird in the barn. He can also subscribe to one of at present 15 available alerts that send messages directly to his mobile phone including a visual map of his barn floor with spots indicating the location from which the alert was triggered.

Results and discussion

Figure 2 shows an example of a broiler barn with an uneven distribution of relative humidity. The reason was a higher animal density in the left part of the barn. More animals mean a higher release of water vapour via the breathing air of the animals and thus higher humidity in the ambient air.

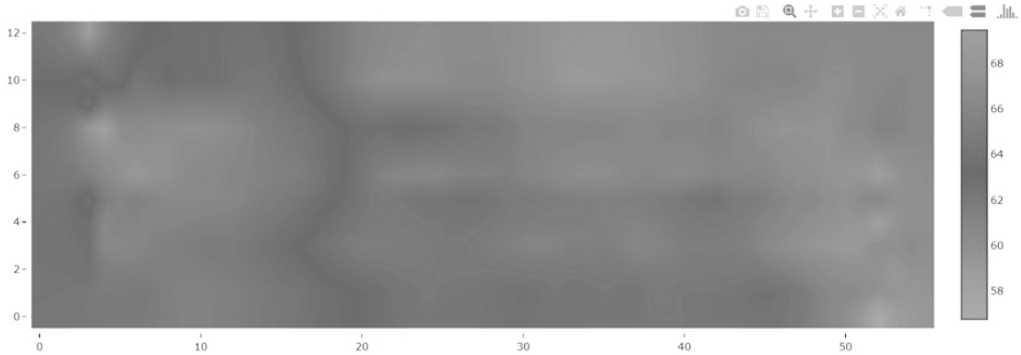

Figure 2. Uneven distribution of rel. humidity in the air of a broiler barn 50 cm above the floor. 14,000 birds, tunnel ventilation from left to right, barn size 55 × 12 m

In Figure 3 the thermal pictures of a living (left) and a dead (right) broiler bird is shown. The combination of the visible and infrared camera can clearly distinguish between dead and viable birds by temperature and position of the animal.

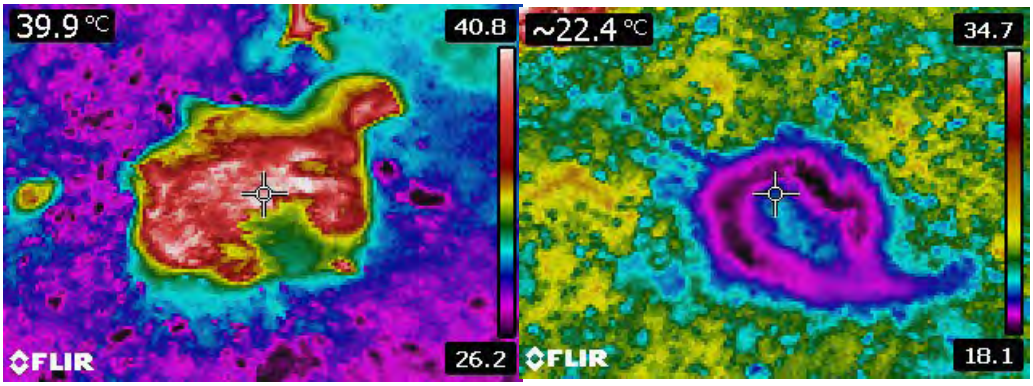

Figure 3. Thermal pictures of a living (left) and a dead (right) broiler bird

Figure 4 shows a resulting map of the measurements carried out by the robot presented to the farmer on his PC or mobile phone. The dots in different colours represent 'bad' faeces (blue), wet spots in the litter (orange), dripping / broken nipples (green), and dead birds (red). This automatic mapping gives the farmer practical advice for his daily work. The careful evaluation of these surveys can give valuable indications of systematic failures in the barn, e.g. when there is a cumulation of dead birds in a certain part of the barn.

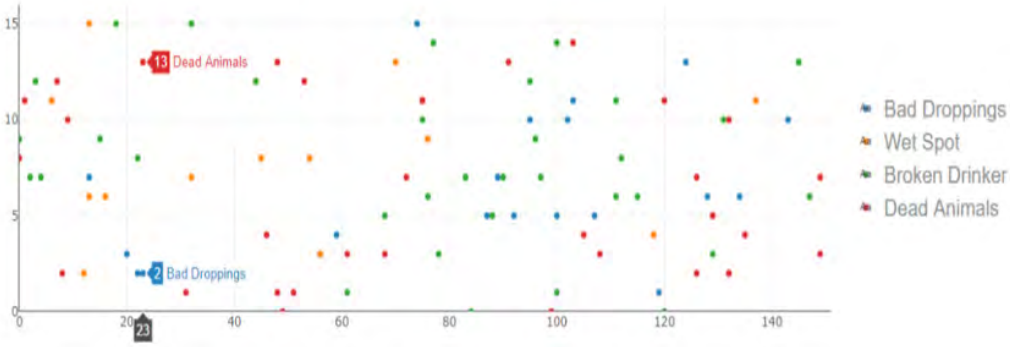

Figure 4. Automatic mapping of ChickenBoy results in a broiler barn with dimensions 140 m × 15 m

Conclusions

The presented example of a precision livestock farming robot has a considerable potential to improve animal welfare and health of broilers by real-time surveillance and transparency of production. It can increase the quality of the life of broilers, satisfy the farmer's need in terms of respected production and reliable income and may help to reconcile consumers with modern production systems.

The system offers a wealth of data by real-time monitoring and direct presentation to the responsible farm worker. Recognising early technical failures, dead birds and the onset of diseases can reduce both suffering of animals and the use of drugs such as antibiotics and can improve production.

Intelligently used, this 4.0 technology can significantly help farmers protecting health, welfare and performance of his animals, reduce losses and may possibly raise acceptance of animal products deriving from modern farming systems in all parts of the society by transparency of production.

By direct and in real-time involvement in the life of his animals, the farmer can develop a better understanding of his animals, which helps him to improve the quality of life of the animals. A European study revealed that most of European farmers are in favour of PLF support systems for their farm animals when they are economically affordable and technically reliable (Hartung *et al.,* 2017).

In future, a closer cooperation between farmers and veterinarians is required. By direct transmission of data and pictures from a farm, the veterinarian can quickly do a preliminary diagnosis and treatment can happen much earlier than usual today.

Acknowledgements

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References

Anonymus (2019). World Animal Protection. Internet accessed March 2019.

Harrison, R. (1964). Animal Machines.

Hartung, J. (2013). A short history of livestock production. In: Aland, A., Banhazi, T. (Hrsg.): Livestock housing: Modern management to ensure optimal health and welfare of farm animals, Wageningen Academic Publishers, The Netherlands, 21–34.

Hartung, J., Banhazi, T., Vranken, E., Guarino, M. (2017). European farmers' experiences with precision livestock farming systems. Animal Frontiers, 7(1), Champaign: American Society of Animal Science, 2017, 38-44 (Journal Article). doi:10.2527/af.2017.0107.

Robinson, T.P., Thornton, P.K., Franceschini, G., Kruska, R.L., Chiozza, F., Notenbaert, A., Cecchi, G., Herrero, M., Epprecht, M., Fritz, S., You, L., Conchedda, G. & See, L. (2011). Global livestock production systems. Rome. Food and Agriculture Organization of the United Nations (FAO) and International Livestock Research Institute (ILRI), pp. 152.

The Economist (2011). 27 July 2011, retrieved March 2019.

Field trial to demonstrate the intelligent dairy assistant (IDA) system on dairy farms

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Abstract

Connecterra's Intelligent Dairy Assistant (IDA) is a novel Internet of Things based on a management support system for dairy farms. IDA uses sensor technology, cloud computing and artificial intelligence to support dairy farmers with insights on oestrus and health management. IDA analyses cow behaviour (originating from a 3D accelerometer on a neck collar) and herd patterns, and learns from the farmer's feedback. Within the Horizon 2020 project Internet for Food and Farm (www.IoF2020.eu) a field trial was conducted. The goal was to demonstrate that the IDA approach to generate actionable insights works. Therefore, we tracked KPI's on farm economics, animal health and fertility on two commercial dairy farms. We report the results of our trial from January to December 2018. Both farms had a herd of 100 cows, from which 50 cows were equipped with IDA. The farm KPI's were measured separately for the groups *with* and *without*. In comparison to the *without* group, the *with* group had, on average, its expected calving interval 5.92 and 0.88 days lower on Farm 1 and 2, respectively. Likewise, treatments with antibiotics 1.15 and 2.60 days shorter and 305 day milk yield 434 kg higher (Farm 1) and 405 kg lower (Farm 2) in the *with* group. For milk production the results are inconclusive as the groups were not balanced on milk yield before the trial started. We experienced in this trial, by qualitative feedback of the farmers, that the IDA approach worked and more observations are needed for scientific proof.

Keywords: sensor, artificial intelligence, learning, oestrus, health

Introduction

In dairy farming trends move to larger herds per farmer, less farmers and lower labour input (Barkema *et al.*, 2015). These trends influence the management of dairy farms dramatically. In order to support the management of dairy farms many sensor systems have been proposed (Rutten *et al.*, 2013; Caja *et al.*, 2016). It has been suggested that sensors can help improve farm profitability, animal health, welfare and fertility impact *(Wathes et al., 2005; Ipema et al.*, 2011; Banhazi *et al.*, 2012). However, uptake of decision support systems by dairy farmers in practice has been limited thus far (Borchers & Bewley, 2015; Steeneveld & Hogeveen, 2015).

Investment analysis on automated oestrus detection has shown inconclusive results. Ex ante simulations have estimated positive returns on investment (Rutten *et al.*, 2014; Dolecheck *et al.*, 2016). On the other hand, the analysis of real farm data did not confirm this result (Steeneveld *et al.*, 2015a). The problem is that it was hard to explain the difference as farmers often made several investments and management changes over the same period (Steeneveld *et al.*, 2015a). Furthermore, there are only a few studies that have attempted to observe and measure technical changes on dairy farms.

The recent improvements in machine learning algorithms, cloud computing and internet of things (IoT) hardware and data communication protocols collectively make it economically feasible to deploy an advanced monitoring solution that can continuously

observe cows every second of the day for multiple years. The acquired accelerometer data sets are sufficiently granular for convolutional neural networks to detect behavioural activities such as eating, ruminating, walking, standing and laying. Since IoT and cloud computing allows the direct interpretation of behavioural data, a farmer can be instantly alerted when a behavioural pattern emerges that indicates a potential health issue. The directly elicited feedback from the farmer allows an innovative automated learning system that can evolve over time to allow an increasingly precise and specific diagnosis of the cow's health and fertility status that would not have been economically feasible without the recent breakthroughs in IoT, A.I. and cloud computing. While real-time sensor systems are in common use by dairy farmers, such systems offer only limited decision support features. New IoT systems can exploit cloud computing to allow for more advanced data analysis techniques, resulting in improved decision-making by the dairy farmer.

The goal of this field trial is to demonstrate that the IDA prototype, based on the approach of using cloud computing and artificial intelligence to interpret data and generate actionable insights, can support dairy farm management in a meaningful way.

Material and methods

In this field trial Connecterra's Intelligent Dairy Assistant (IDA) was used. IDA is a novel IoT-based management support system for dairy farms. IDA uses sensors, cloud computing and artificial intelligence to support dairy farmers management. IDA analyses cow behaviour (originating from a 3D accelerometer on a neck collar) and herd patterns, and learns from the farmer's feedback. In this field trial, two commercially available features of IDA were tested, detection of oestrus and detection of health problems. IDA presents actionable insights rather than data or graphs to the farmer. The farmer reviews the insight, checks the cow and takes the appropriate measures and responds back to IDA through an app or web application. In this field trial the farmers have agreed to actively use the app, i.e. check and respond to each insight. The Horizon 2020 project Internet of Food and Farm (IoF 2020) gives the opportunity to demonstrate and test IoT based applications in practice. Within this context we could provide 50 sensors to two farmers in 2018. For this trial two farms with a herd size of 100 cows were selected in Belgium and the Netherlands.

The two herds were split into two groups, one with and one without IDA. The selection was semi random while it was stratified for lactation number and fertility state (open, pregnant and dry). The assumption is that better monitoring of the *with IDA* group will help the farmers to detect oestrus and health issues earlier and thereby improve management for this group. Because the herd was split into two groups, the idea is that there are two comparable groups. Therefore, KPI's were defined, benchmarked and tracked over time. The benchmark at the start of the experiment was to evaluate whether the farm as a whole did improve over time, e.g. because the farmers increases his skills or capacity with the use of IDA. Data collection took place for 12 months, starting at January 2018. For each farm, the most recent year from January to December in which the respective farmer was not using IDA was chosen as a benchmark. Since IDA was deployed at Farm 1 during 2017 for another trial, the year 2016 was chosen as a benchmark at Farm 1. The year 2017 was chosen as a benchmark year for Farm 2. For both farms, the farm structure and herd sizes did not change since the benchmark year.

Three KPI's were defined and based on readily available data from the farm management system. Firstly, the production level of the cows was monitored with the 305 day milk production that originates from the milk production registration. Secondly, the expected calving interval was estimated. The insemination dates and pregnancy checks were used to determine if a cow was successfully inseminated. To estimate an expected calving

interval an average gestation length of 280 days (Parkinson *et al.*, 2001) was assumed. Thirdly, antibiotic use was monitored as the number of days that a cow was treated in the past year. Each month data were pulled from the farm management system to estimate these KPI's. The moving average over a year was taken to exclude small fluctuations that can occur on a month to month basis. For all three KPI's the average value per KPI was for the groups *with IDA* and *without IDA* separately.

Results and discussion

In Figure 1, the KPI's for Farms 1 and 2 are presented per month of the experiment. On Farm 1 the expected calving interval was on average 5.92 days shorter for the *with IDA* group. However, in months 7, and 9–12 the *without IDA* group had a shorter expected calving interval ranging from 2–15 days. We have no clear explanation to why the *without IDA* group had a shorter expected calving interval for these months in the second half of 2018. It will be interesting to see how the trend develops in the next year of the trial. Both groups at Farm 1 had a significantly shorter expected calving interval of 77 and 68 days in comparison to the benchmark year for the *with IDA* group and *without IDA* group, respectively. The 305 day milk yield was on average higher for the *with IDA* group and the difference with the *without IDA* group increased over the course of the trial. For both groups the 305 day yield was more than 200 kg / 305 days / cow higher than the average of the benchmark year 2016. The comparison to the benchmark indicates that the farmer did improve his herd or his herd management over time. The use of antibiotics was consistently lower for the group *with IDA* than for the group *without IDA*. On average the treatment with antibiotics in the *without IDA* group took twice as long as the *with IDA* group.

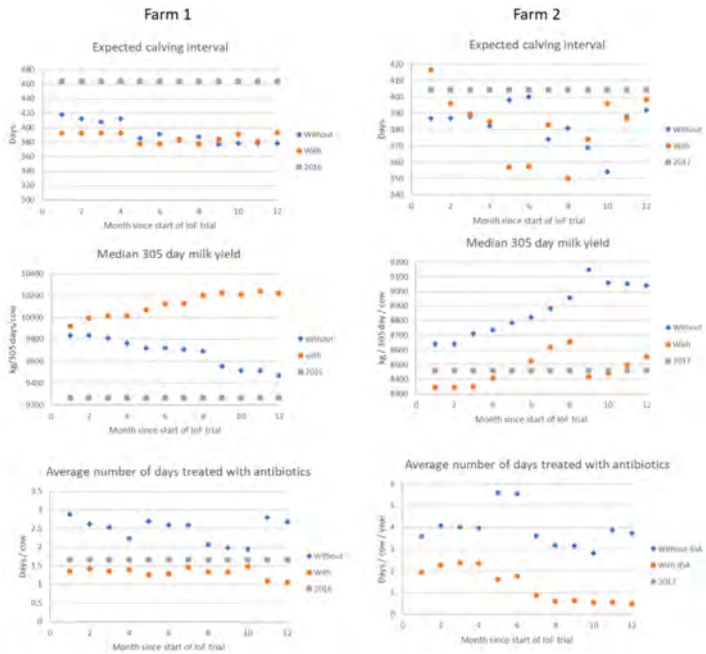

Figure 1. KPI's on expected calving date, 305 day milk yield and antibiotics use measured on two farms for groups with and without IDA and compared to a benchmark (the previous year in which no cow had IDA)

On Farm 2 the expected calving interval varies over time for both groups. We do not see a clear difference between the with and without group. The 305 day milk yield was higher for the group without IDA and it remained higher over the course of the trial. This observation is in line with the feedback we received from Farmer 2. Our selection method did not stratify for production level, so, the farmer noted that of his best cows none were selected for the IDA group. The yield for both the with and without group did increase over time. No positive effect of IDA on milk yield can be deduced from the data of Farm 2. The antibiotic use on Farm 2 was consistently lower for the group with IDA than for the group without. The average duration of antibiotic treatment in the *with IDA* group shortened during the trial. On average, the duration of antibiotic treatment in the control group lasted four times longer than the group with IDA. Our observations on antibiotics use are in line with the feedback of Farmer 2. Farmer 2 noted that IDA detected a cow with *e. coli* earlier than the farmer did for cows without IDA and thereby could start treatment earlier and a shorter treatment than normal was sufficient. For Farm 2 we were unable to retrieve the antibiotic use data prior to the start of our field trial.

In this field trial we observed differences between the with and without groups and these observations are in line with the feedback we gathered from the farmers. However, we cannot prove a causal relationship between the use of IDA and the observed changes in the KPI's. The number of cows and farms are too low to show causal relationships, but are big enough to demonstrate practical use and first impressions. Furthermore, the selection of cows was not balanced for milk yield and this fact may influence reproductive efficiency and health of the *with* and *without* groups. In general, milk yield has been observed to reduce the odds of conception and increase the risk on disease. For the reduction in antibiotic use, we have anecdotical evidence that our approach enables early detection of diseases. Furthermore, this anecdote indicates that farmers are able to start earlier with more effective treatments. We have no evidence to support a generalised claim on the potential of early detection, early and effective treatment. That will require more in-depth studies on multiple diseases. For instance, experiments on the effectiveness of early hoof trimming of sub clinically lame cows, and the willingness and ability of farmers to apply such an intervention in practice.

Automated oestrus detection has been suggested to improve oestrus detection rate especially for larger herds or when limited amounts of labour are available (Firk *et al.*, 2003; Kamphuis *et al.*, 2012). A better oestrus detection rate would result in a shorter calving interval and have financial gains (Inchaisri *et al.*, 2011; Rutten *et al.*, 2014). The situation on Israeli dairy farms seems to confirm the idea that automated oestrus detection improves reproductive efficiency (Galon, 2010). However, a Dutch study on real farm data contradicts those findings (Steeneveld *et al.,* 2015b). Our study observes some positive effects on oestrus detection and calving interval, but differences are small and far from conclusive yet. Our trial was not a fully controlled experiment as it involved only two commercial dairy farms. Therefore, it is possible that our assumption of an equal breeding strategy across the whole herd may not be valid, e.g. the farmer uses a shorter voluntary waiting period for the group with IDA.

On Farm 1 we found indications that the group with IDA had a higher production level than the group without IDA. The root causes of these effects were not investigated. But based on literature we could speculate that better management helps cows reach their full potential. Firstly, automated measurement of rumination behaviour can be used to monitor dairy cows health, e.g. ruminal acidosis and heat stress (Beauchemin, 2018). For heat stress it seems questionable whether a farm could take measures to mitigate heat stress for an individual cow. Heat stress depends strongly on weather, which a farmer

cannot influence and barn climate, which a farmer could influence but would affect the whole herd equally. However, studies suggest potential to optimise concentrate feeding that balances energy balance and acidosis risk based on rumination data of individual dairy cows (King *et al.*, 2018).

Secondly, lame cows have been described to eat, walk and ruminate less and to lay more (Kramer *et al.*, 2009; Ito *et al.*, 2010; Miekley *et al.,* 2012). These behaviours are associated with a lower milk yield as is also observed for lame cows (Ettema and Østergaard, 2006; Bruijnis *et al.*, 2010). Therefore, it would seem plausible that IDA could detect cows with aberrant behaviour and thereby enable the farmer to intervene.

Previous research has suggested benefits from individually optimised treatments (Hogeveen *et al.*, 2010; Steeneveld *et al.*, 2011). Health monitoring is believed to enable early detection of diseases and thereby enable early treatment (Løvendahl and Friggens, 2009; Hogeveen *et al.*, 2010; Rutten *et al.*, 2013). Although widely suggested this benefit of early detection has never been confirmed in experiments. Our field trial does provide some first indications of the value that sensors have for early detection and treatment of diseases. The lower antibiotics use for the group with IDA and the farmer feedback indicate that sensor monitoring could have a positive effect on the treatment effectiveness for dairy cows. However, our study does not provide causal evidence yet to support this theory, it merely illustrates observed differences on a commercial dairy farm.

It has been widely suggested that more detailed herd information from sensors would enable better management decisions (Wathes *et al.*, 2005; Ipema *et al.*, 2011; Banhazi *et al.,* 2012). However, such effects on herd level could not be observed in our trial. In this field trial we use two herds which we split in two groups. This ensures that circumstances like barn setup, climate and milking routine were the same for all cows. The advantage is that the two groups can be more easily compared, because it seems appropriate to assume that there are no external factors causing differences between the two groups. However, it could also cause a limitation, because all cows would be subject to the same herd management like the mixed ration the cows are fed, and the fact that the farmer might be influenced by the experiment and the IDA system, and that he is projecting that on the *without IDA* group. So, in our trial we cannot asses the full potential of the IDA system to help dairy farmers improve their management.

Conclusion

For milk production the results are inconclusive as the groups with and without IDA were not balanced on milk yield before the field trial started. We experienced by qualitative feedback of the farmers that the IDA approach works. The experiences indicate that oestrus detection can be improved and health monitoring can help to start early treatment and thereby reduce the use of antibiotics. In this field trial we demonstrated positive changes in milk production, calving interval and antibiotics use. Based on the limited size of the experiment we could not prove significant effects or causal relationships.. The IDA system uses feedback on historic data to improve its underlying models and farmers may learn from using the system. We therefore look forward to how the tracked KPI's will evolve in the successive year and if farm management will be further improved.

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References

Banhazi, T.M., H. Lehr, J.L. Black, H. Crabtree, P. Schofield, M. Tscharke, and D. Berckmans. (2012). Precision Livestock Farming: an international review of scientific and commercial aspects. *International Journal of Agricultural and Biological Engineering,* 5: 1–9.

Barkema, H.W., M.A.G. von Keyserlingk, J.P. Kastelic, T. Lam, C. Luby, J.P. Roy, S.J. LeBlanc, G.P. Keefe, and D.F. Kelton. (2015). Invited review: Changes in the dairy industry affecting dairy cattle health and welfare. *Journal of Dairy Science,* 98: 7426–7445.

Beauchemin, K.A. (2018). Invited review: Current perspectives on eating and rumination activity in dairy cows. *Journal of Dairy Science,* 101: 4762–4784.

Borchers, M.R., and J.M. Bewley. (2015). An assessment of producer precision dairy farming technology use, prepurchase considerations, and usefulness. *Journal of Dairy Science,* 98: 4198–4205.

Bruijnis, M.R.N., H. Hogeveen, and E.N. Stassen. (2010). Assessing economic consequences of foot disorders in dairy cattle using a dynamic stochastic simulation model. *Journal of Dairy Science,* 93: 2419–2432.

Caja, G., A. Castro-Costa, and C.H. Knight. (2016). Engineering to support wellbeing of dairy animals. *Journal of Dairy Research,* 83: 136–147.

Dolecheck, K.A., G. Heersche Jr, and J.M. Bewley. (2016). Retention payoff–based cost per day open regression equations: Application in a user-friendly decision support tool for investment analysis of automated estrus detection technologies. *Journal of Dairy Science,* 99: 10182–10193.

Ettema, J.F., and S. Østergaard. (2006). Economic decision making on prevention and control of clinical lameness in Danish dairy herds. *Livestock Science,* 102: 92–106.

Firk, R., E. Stamer, W. Junge, and J. Krieter. (2003). Oestrus detection in dairy cows based on serial measurements using univariate and multivariate analysis. Arch. Fur Tierzucht-*Archives of Animal Breeding,* 46: 127–142.

Galon, N. (2010). The Use of Pedometry for Estrus Detection in Dairy Cows in Israel. *Journal of Reproductive Development,* 56: S48–S52.

Hogeveen, H., I. Chaidate, and W. Steeneveld. (2010). Economic Benefits of Individual Cow Management. Page in *The First North American Conference on Precision Dairy Management*, Toronto, Canada.

Inchaisri, C., R. Jorritsma, P. Vos, G.C. van der Weijden, and H. Hogeveen. (2011). Analysis of the economically optimal voluntary waiting period for first insemination. *Journal of Dairy Science,* 94: 3811–3823.

Ipema, A.H., E.J.B. Bleumer, and C. Lokhorst. (2011). Precision Livestock Farming claims for Sustainable Dairy Production. Pages 271–280 in 5th European Conference on Precision Livestock Farming. Czech Centre for Science and Society, Prague, Czech Republic.

Ito, K., M.A.G. von Keyserlingk, S.J. LeBlanc, and D.M. Weary. (2010). Lying behavior as an indicator of lameness in dairy cows. *Journal of Dairy Science,* 93: 3553–3560.

Kamphuis, C., B. DelaRue, C.R. Burke, and J. Jago. (2012). Field evaluation of 2 collar-mounted activity meters for detecting cows in estrus on a large pasture-grazed dairy farm. *Journal of Dairy Science*, 95: 3045–3056.

King, M.T.M., K.J. Sparkman, S.J. LeBlanc, and T.J. DeVries. (2018). Milk yield relative to supplement intake and rumination time differs by health status for fresh cows milked with automated systems. *Journal of Dairy Science*, 101: 10168–10176.

Kramer, E., D. Cavero, E. Stamer, and J. Krieter. (2009). Mastitis and lameness detection in dairy cows by application of fuzzy logic. *Livestock Science,* 125: 92–96.

Løvendahl, P., and N. Friggens. (2009). Opportunities for online monitoring of health and performance in dairy cows. Recent Advances in Animal Nutrition. Nottingham University Press, [Lovendahl, Peter; Friggens, Nic] Univ Aarhus, Dept Genet & Biotechnol, Fac Agr Sci, DK-8000 Aarhus C, Denmark. Lovendahl, P (reprint author), Univ Aarhus, Dept Genet & Biotechnol, Fac Agr Sci, DK-8000 Aarhus C, Denmark.

Løvendahl, P., C. Ridder, and N.C. Friggens. (2010). Limits to prediction of energy balance from milk composition measures at individual cow level. *Journal of Dairy Science,* 93: 1998–2006.

Miekley, B., I. Traulsen, and J. Krieter. (2012). Detection of mastitis and lameness in dairy cows using wavelet analysis. *Livestock Science,* 148: 227–236.

Parkinson, T.J., G.C.W. England, and G.H. Arthur. (2001). Chapter 6 - Parturition and the care of parturient animals A2 - Noakes, David E.W.B. Saunders, Oxford.

Rutten, C.J., W. Steeneveld, C. Inchaisri, and H. Hogeveen. (2014). An ex ante analysis on the use of activity meters for automated estrus detection: To invest or not to invest?. *Journal of D*airy Science 97:6869–6887. doi:10.3168/jds.2014–7948.

Rutten, C.J., A.G.J. Velthuis, W. Steeneveld, and H. Hogeveen. (2013). Invited review: Sensors to support health management on dairy farms. *Journal of D*airy Science, 96: 1928–1952. doi:10.3168/jds.2012–6107.

Steeneveld, W., and H. Hogeveen. (2015). Characterization of Dutch dairy farms using sensor systems for cow management. *Journal of D*airy Science, 98: 709–717. doi:10.3168/jds.2014–8595.

Steeneveld, W., H. Hogeveen, and A. Lansink. (2015a). Economic consequences of investing in sensor systems on dairy farms. *Comput. Electron. Agric*., 119: 33–39. doi:10.1016/j.compag.2015.10.006.

Steeneveld, W., J.C.M. Vernooij, and H. Hogeveen. (2015b). Effect of sensor systems for cow management on milk production, somatic cell count, and reproduction. *Journal of D*airy Science, 98:3896–3905. doi:10.3168/jds.2014–9101.

Steeneveld, W., T. van Werven, H.W. Barkema, and H. Hogeveen. (2011). Cow-specific treatment of clinical mastitis: An economic approach. *Journal of D*airy Science, 94: 174–188. doi:10.3168/jds.2010–3367.

Wathes, C.M., H.H. Kristensen, J.M. Aerts, and D. Berckmans. (2005). Is Precision Livestock Farming an Engineer's Daydream or Nightmare, an Animal's Friend or Foe, and a Farmer's Panacea or Pitfall? S. Cox, ed. Wageningen Academic Publishers, Silsoe Res Inst, Silsoe MK45 4HS, Beds, England. Wathes, CM (reprint author), Silsoe Res Inst, Wrest Pk, Silsoe MK45 4HS, Beds, England.

An automatic data acquisition system for acquiring training data for a deep learning algorithm for individual cow intake prediction

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Abstract

Individual feed intake of dairy cows is an important, currently unavailable, variable in commercial dairies. Earlier systems developed were either costly or unreliable enough for commercial farms. This research developed a low-cost individual feed intake system using RGB-D cameras and deep learning algorithm. Depth and colour images are produced from an RGB-D camera, and are used to build a CNNs (Convolutional Neural Networks) regression model for weight intake prediction. To provide training data, an automatic data acquisition system was designed to collect a wide range of food weights, in different configurations and conditions (indoor, outdoor, direct-sun). The system included a scale and a micro-controller set in the Volcani research dairy facility, an open cowshed with Holstein cows, eating Total Mix Ration. With this setup, 28,761 data were collected over seven days. Additional data were created by data augmentation methods. The model was evaluated on a test-dataset acquired in the same dairy farm. The model was tested for different combinations of training data (direct-sun/outdoor) to evaluate the importance of the data diversity. Per meal, mean absolute and square errors were 0.127 kg, and 0.034 kg^2, respectively, the consumed amount of feed measured in range of 0-8 kg. The sensitivity analysis shows that the amount and diversity of data is important for model training. Better results were achieved for the model that was trained with high diversity data. The results suggest that cameras and CNNs are feasible for individual feed intake measurement on the dairy farm.

Keywords: individual cow feed intake, 3D camera, machine vision, deep learning, precision livestock farming (PLF)

Introduction and background

Individual feed intake of dairy cows is an important variable in dairy management. Proper measurement of feed intake of cows can help in monitoring individual cow health and productivity. This may increase overall productivity of the farm (Buza *et al.*, 2014; Halachmi *et al.*, 2016; Herd *et al.*, 2003). Researchers have tried to evaluate feeding weight with machine vision systems cameras (Shelley, 2013). Previous studies have attempted to estimate the weight of the food pile using depth cameras by calculating the volume of points cloud received directly from the camera. These studies found it difficult to achieve reliable results due to sunlight interference with the infrared sensor of the cameras (Borchersen *et al.*, 2018). Other studies have shown reasonable predictability but in very specific lighting conditions, using Light Detection and Ranging (LIDAR) sensing methods (Shelley *et al.*, 2016). A recent study attempted to overcome the problem of sunlight by using photogrammetry methods (Bloch *et al.*, 2019). This method requires multiple high quality RGB cameras per food pile measurement, scattered at different observation points to build a point cloud of the food pile. Although this method showed better results, the estimation error for calculating the mass was 0.483 kg for heaps up to 7 kg. The SD for the estimation error for the cowshed experiment was 0.44 kg, resulting in total method error of 1.32 kg for heaps up to 40 kg. Another major weakness of this approach is that the coloured markers used for the point cloud processing would not be applicable in a

cowshed on a working farm (dirt can change the colours and they can be inadvertently detached from the floor and walls by tractors).

In recent years there has been significant development in computer vision systems, thanks to deep learning methods. Deep learning or officially deep Convolutional Neural Networks (CNNs) is a discipline that belongs to the machine learning family, and is useful for complicated computer vision tasks such as detection, classification, recognition, and tracing. The CNNs are inspired from the learning process of neurons in the human brain. This method has become popular and available in recent years because of the growth of computer computation capability of Graphics Processing Units (GPUs), and the amount of available data in the world of big data (Chen & Lin, 2014). CNNs are based on highly non-linear, end-to-end training, which implies the learning of millions of parameters and, accordingly, they require relatively large amounts of diverse and annotated data (Ros *et al.*, 2016).

This study deals with building a CNNs regressor model for predicting feed intake using an RGB-D camera. In order to obtain a reliable model, the CNNs regressor must rely on large and varied labelled data collected from the RGB-D camera, and the corresponding weight of the food pile images. Since the desired output in the prediction is a continuous value and the data is presented as two images – depth image and colour image, the images collection, together with labelling process, is a difficult task; especially when large-scale data is needed. The diversity of the data determines the robust and generic value of the model. Therefore, data collection is one of the most important operations for building a CNNs regressor. The high variance between different dairy farms in a multitude of parameters (e.g. geographic orientation, background features like shape and colour, lighting power and its influence on depth data) can be an obstacle to achieve a model that can be useable everywhere. Furthermore, the model must be immune to weather influence.

To estimate how much a cow ate at a specific meal, information about the food pile after the meal should be subtracted from information about the pile before the meal. The first intuitive thought to solve this problem is to train a CNNs model that predicts the weight of a single food pile. This model can predict the weight of the food before and after the meal, and then calculate the difference between the two prediction values. However, this metric contains several problems. First, as discussed, for building a CNNs model large datasets are necessary, especially if the required prediction values include a continuous range between 0 and 30 kg. Second, since there can be very high variability in the dispersal of a single food pile in any weight range, this may lead to error predictions. Third, assuming that each prediction has an error, if the desired result depends on two predicted values, the calculated result may contain a high bias.

This study presents a possible solution to provide and create a data set, by designing an automated acquisition system, and a subtraction method to increase the amount of data. This data is used to train a CNNs model for cow feed intake weight prediction of a single meal, using an RGB-D low cost camera.

Materials and methods

Weight calculation

Depth and colour images (Figure 1) are produced from an RGB-D camera, which is placed 1.4 meters above the ground of the feeding area. These images are used to build a CNNs regression model for weight intake prediction.

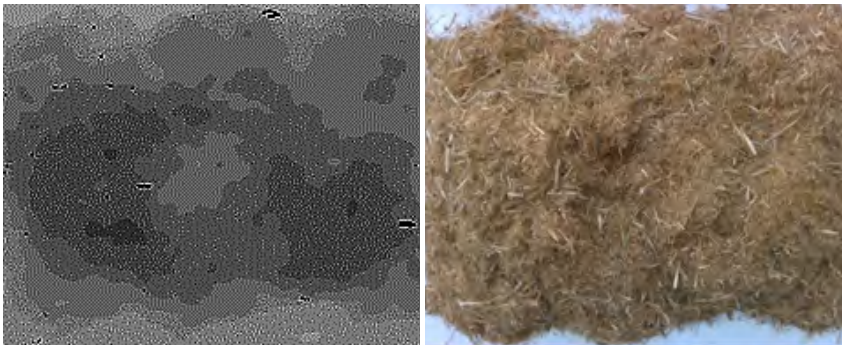

Figure 1. Left - depth image; right - RGB image

Data collection setup for weight prediction

We developed an automated data collecting system to achieve a convenient way to collect data under different conditions. The system consists of a 3D camera, weight, Arduino micro-controller and computer; on the top of the weight we installed a large plate. All these components were installed in an aluminium frame setup, so the camera was situated directly above the weight palette (Figure 2).

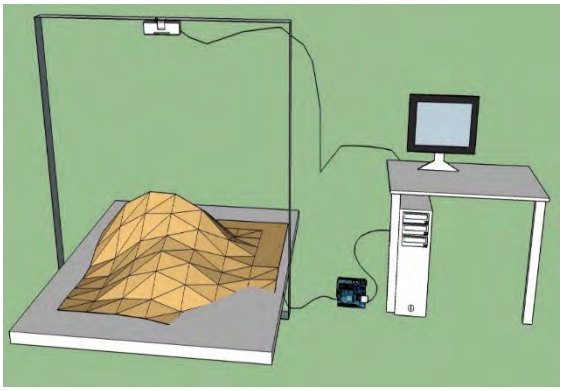

Figure 2. Data acquisition system

The micro-controller is connected to the scale and streams the weight readings to the computer. Simultaneously, the 3D camera streams RGB and depth images on two different tracks to the same computer (Figure 3). The user can change the shape of the food pile as desired and save the data – RGB image, depth image, and their weight label – on a data structure.

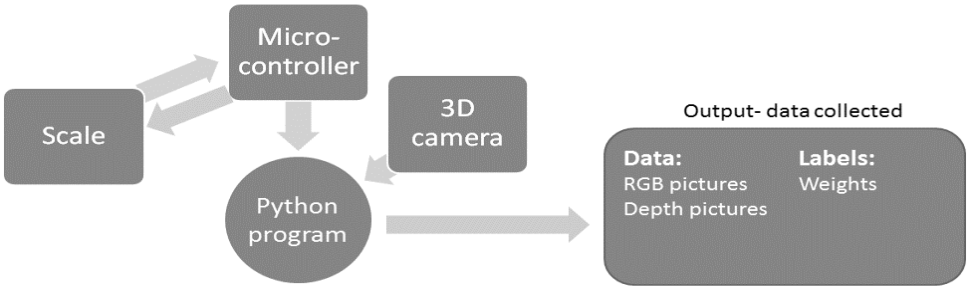

Figure 3. Data acquisition structure designing

994 depth and RGB images were acquired in the weight range of 0–30 kg (Table 1). The data were collected for a wide range of setups including different backgrounds (standard, brown, as exists in the dairy farm) and illumination (standard, covered, direct sun, shadows) in both indoor and outdoor conditions.

Table 1. Data collected

Session	Condition	Location	Background	Samples
1	standard	indoor	standard	74
2	covered	indoor	standard	391
3	covered lights	indoor	brown	177
4	shadow	outdoor	standard	140
5	direct sun	outdoor	standard	95
6	shadow	outdoor	dairy farm	39
7	shadow	outdoor	dairy farm	78

Create a dataset for weight consumed prediction

In order to create a dataset that is not sensitive to the description in the background section, and includes all the required information to solve the problem, we built a new dataset including tensors based on the collected data. This tensor contains the result of the difference between two food pile images, before and after the meal, representing the feed intake (Figure 4). Unlike standard image subtraction, which results in a tensor with no negative values (i.e. that is zero in any negative pixel subtraction result), this subtraction preserves negative values. These values can be obtained when the cow moves the food during feeding. This way we keep all the information related to the difference between the two images.

Figure 4. Illustration of subtraction of colour images. Pile of 3.49 kg subtracted from pile of 12.22 kg. The resulting tensor represents 8.73 kg

To create the dataset, the following was conducted: all images of each food pile were subtracted from all the images with a reduced weight value (Formula 1). The subtraction

$$Tensor_{i,j} = Image_i - Image_j \ \forall\ i,j \text{ were } Weight(Image_i) > Weight(Image_j) \quad (1)$$

works on four channels separately (RGB and Depth). Thanks to this method, the amount of the training data increases proportionally to the sum of arithmetic sequence.

To further increase the dataset for training, we also performed rotational flipping augmentations before images subtraction, so that from each subtraction of images, four completely different images emerge (Figure 5). Finally, for some of the subtracted tensors, additional rotational and flipping augmentations were also performed. To reserve the balance and uniformity of the data for the model training phase, we made sure to produce a balanced number of data to represent single meals (as described above) in each value range [0,8] in the artificial data creation step. The number of samples created was 28,761 in four-channel matrices, 20% of the data was used for testing and 80% for training and validation.

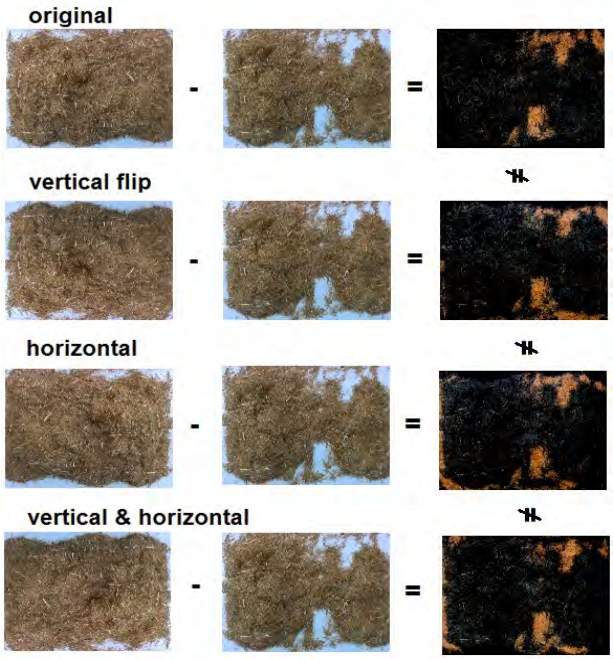

Figure 5. Illustration rotational flipping augmentations before images subtracting

Testing data

The model was tested on an independent dataset taken from the research dairy farm, by using the developed data collection setup. Seventy-eight food pile images, simulating a feeding station with range of 0–30 kg, were acquired in an outdoor setting. From these images a dataset that simulates 576 single meals was assembled.

CNNs Regressor model

The CNNs model was trained on the RGB-D data, which included a tensor of 4-channel matrices of data, each with 480 × 640 pixels. The model design was inspired by ResNet CNNs (He *et al.*, 2016). In ResNet, the input of a convolutional layer bypasses one or

more layers, and is added to the outputs of forward layers (Figure 6), denoted as residual mappings. Since the information is directly transmitted, the ResNet architecture avoids a vanished gradient, enabling easier learning even with deeper structures (He *et al.*, 2016). The model developed for feed intake prediction used the residual blocks with 20 layers of 3 × 3 convolution kernels.

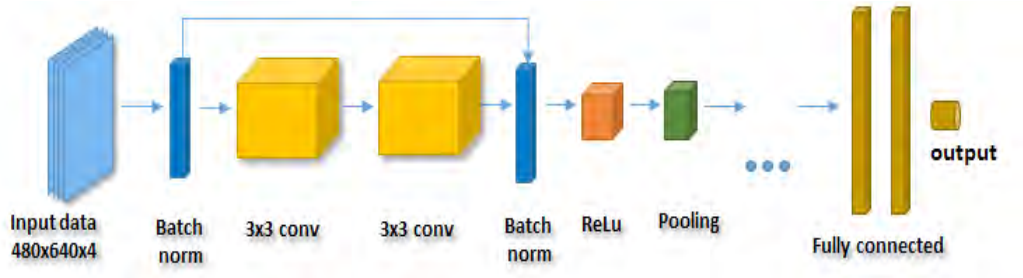

Figure 6. ResNet architecture

Results and discussion

Feeding weight prediction

The weight CNNs regressor measures consumed feed in range of 0-8 kg per meal. Results revealed food predictability (Figure 7) with a prediction mean absolute error (MAE) of 0.127 kg per meal, and a mean square error (MSE) of 0.034 kg^2 per meal. The total error was 12 kg from 2 tons distributed over the test data samples.

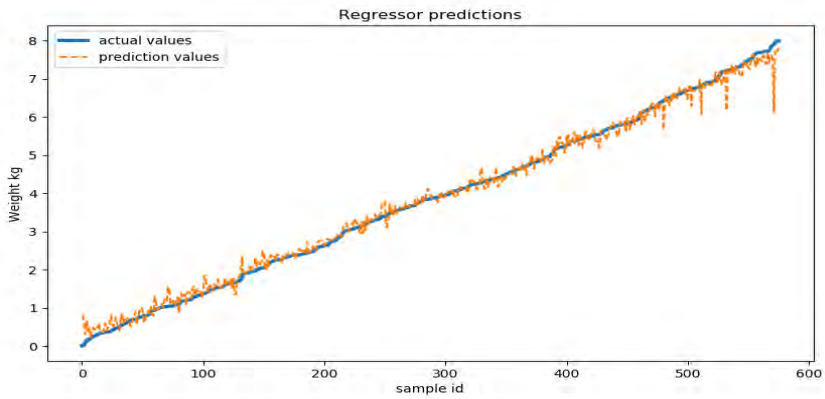

Figure 7. Weight prediction graph based on all training data. The observations are arranged in ascending order on the X-axis, according to the actual value; the Y-axis is the weight in kg

Sensitivity analysis of data diversity

In order to demonstrate the necessity of data diversity with large scale, we trained more models based on part of the data, and tested them on the test set. Model 1 was trained on 6,964 shadow conditions data, and Model 2 was trained on 6,888 direct sun condition data. The results of Model 1 weight prediction (Figure 8) were MAE of 0.761 kg per meal, and MSE of 0.996 kg^2 per meal.

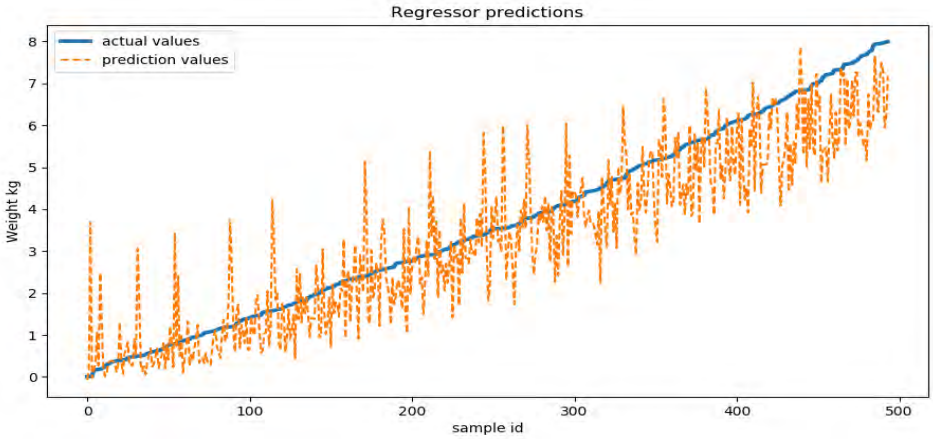

Figure 8. Weight prediction graph based shadow data. The observations are arranged in ascending order on the X-axis, according to the actual value; the Y-axis is weight in kg

The results of Model 2 weight prediction were even worse (Figure 9), with a prediction MAE of 1.504 kg per meal, and a MSE of 4.802 kg^2 per meal.

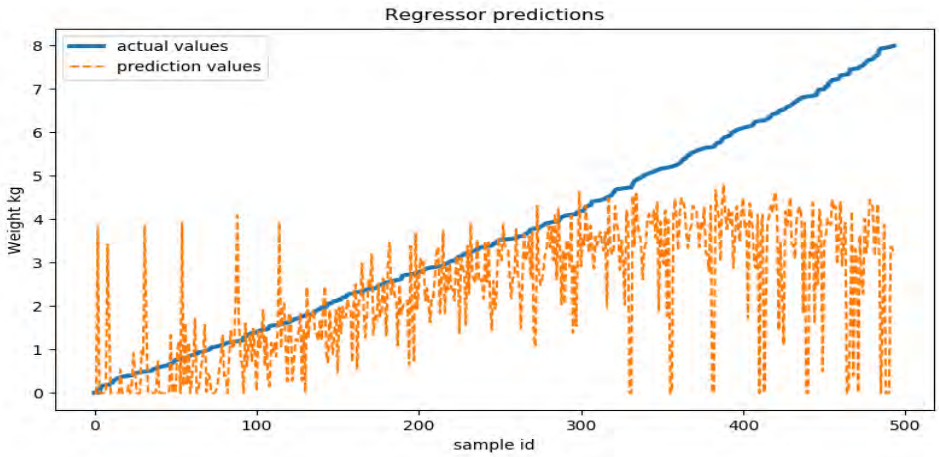

Figure 9. Weight prediction graph based on direct sun data. The observations are arranged in ascending order on the X-axis, according to the actual value; the Y-axis is weight in kg

As can be seen in Table 2, diversity and the amount of data is important for model training. Better results are achieved for the model that has been trained with high diversity data.

Table 2. Models results comparison

Training data	Amount of data	MAE in kg	MSE in kg^2
All conditions	23,000	0.127	0.034
Only shadow condition	6,964	0.761	0.996
Only direct sun condition	6,888	1.504	4.802

Conclusions

Results of the simulated cow feed intake prediction shows high accuracy in the open-cowshed test dataset, with Mean Absolute Error of 0.127 kg, and Mean Square Error of 0.034 kg^2 per meal. This is better than state-of-the-art estimation error achieved by the photogrammetry method (0.483 kg for heaps up to 7 kg). The model showed success in open-cowshed, despite the use of an RGB-D camera that is sensitive to external conditions. This success is due to the specially created training set that provides highly variable data for the deep learning algorithm that overcomes the variable conditions. The developed model proves the feasibility of the system without requiring mechanical accessories. Ongoing research aims to apply this algorithm for real-time feed intake detection for each individual cow.

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References

Bloch, V., Levit, H. and Halachmi, I. (2019). Monitoring Individual Feed Intake of Cattle using Photogrammetry. *Journal of Dairy Research,* 1–6.

Borchersen, S., Hansen, N.W. and Borggaard, C. (2018). System for determining feed consumption of at least one animal. United States patent US9861081B2.

Buza, M.H., Holden, L.A., White, R.A. and Ishler, V.A. (2014). Evaluating the effect of ration composition on income over feed cost and milk yield. *Journal of Dairy Science,* 97(5): 3073–3080.

Chen, X.W. and Lin, X. (2014). Big data deep learning: challenges and perspectives. *IEEE Access* 2, 514–525.

Halachmi, I., Meir, Y.B., Miron, J. and Maltz, E. (2016). Feeding behavior improves prediction of dairy cow voluntary feed intake but cannot serve as the sole indicator. *Journal of Animal Science,* 10(9): 1501–1506.

He, K., Zhang, X., Ren, S. and Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Las Vegas, NV, pp. 770–778.

Herd, R.M., Archer, J.A. and Arthur, P.F. (2003). Reducing the cost of beef production through genetic improvement in residual feed intake: Opportunity and challenges to application. *Journal of Animal Science*, 81(13): 9–17.

Ioffe, S. and Szegedy, C. (2015). Batch normalization: Accelerating deep network training by reducing internal covariate shift. *arXiv preprint arXiv:1502.03167*.

Ros, G., Sellart, L., Materzynska, J., Vazquez, D. and Lopez, A.M. (2016). The synthia dataset: A large collection of synthetic images for semantic segmentation of urban scenes. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Las Vegs, NV, pp. 3234–3243.

Shelley, A.N. (2013). Monitoring Dairy Cow Feed Intake Using Machine Vision. Ph.D. dissertation, Electrical and Computer Engineering, University of Kentucky.

Shelley, A.N., Lau, D.L., Stone, A.E. and Bewley, J.M. (2016). Short communication: Measuring feed volume and weight by machine vision. *Journal of Dairy Science,* 99(1): 386–391.

Technological tools for infection detection: Case studies with the SOMO respiratory distress monitor in Belgian pig farms

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Abstract

For economic reasons, the number of animals per farm(er) has increased drastically over the last decades and will continue to rise further in the future. Due to this trend, it has become impossible for farmers and veterinarians to observe large herds intensively on a frequent basis. However, fast detection and identification of infections remains extremely important to optimise the economic result of livestock production, the welfare of the animals and the reduction of the overall use of antibiotics. These challenges are the drive behind the continuous growth of the precision livestock farming sector where advanced technologies are used to optimize the contribution of each animal. In this study, the SOMO Respiratory Distress Monitor of Soundtalks was used as a commercially available product with an early warning tool for the automated detection of respiratory problems in fattening pig houses. Based on the continuous processing of the sounds recorded in a pig barn, SMS or e-mail notifications were sent from the SoundTalks cloud to farmers and veterinarians. In a demonstration project in Flanders (Belgium), the SOMO was installed in 10 commercial fattening pig houses showing an automatic alarm when respiratory problems occurred. During the demonstration period of two years, one or two SOMO devices were installed in four identical pig house compartments in all 10 farms. The warnings of the SOMO-system were analysed against the observations of the farmer. In total, 72 cough alerts occurred on which farmers gave feedback. The management decisions to tackle the alarm situations were taken by the farmer in consultation with his veterinarian. This study mentions the challenges that came along with the collection and processing of data from the different livestock facilities, including suggestions from farmers and local vets. This valuable information was used to translate the data from the systems into more advanced customised information by automated analysis.

Introduction

Respiratory diseases are an important cause of increased mortality rate and reduced production performance in intensive pig farming (Chung *et al.*, 2013). Due to respiratory diseases, pig farmers suffer from severe economic losses and the welfare of the animal is impaired. To reduce the negative impact of such diseases, early treatment is requisite. Before early treatment can be started, early recognition of the disease is needed.

Today, the detection of diseases is mostly a task for the farmer. During his daily routine, the farmer visually inspects his animals and the detection of diseases is based on the judgement and experience of the farmer (Berckmans, 2004). Due to the increase in the number of animals per farm, the work load increased, which makes it more difficult for the farmer to monitor each animal accurately.

A solution for monitoring the animals is using automated sensing techniques such as microphones and cameras to detect abnormalities in the behaviour of the animals. Sensing techniques have the ability to monitor the animals continuously and automatically in real-time. This happens without inducing additional stress to the animals. By monitoring

the animals continuously and using appropriate algorithms to detect deviating behaviours or sounds, more information is gathered compared to the snapshot that farmer gets from his daily visual inspection.

Monitoring animals with the use of sound analysis is not new. In 1999, Van Hirtum already monitored cough in pigs (Van Hirtum *et al.*, 1999). Later, SoundTalks developed a commercial device, which monitors the respiratory distress in pigs similar to the work of Vandermeulen *et al.,* 2013. This device is called the SOMO (SOund MOnitor) respiratory distress monitor.

This study covers a field demonstration of the SoundTalks SOMO respiratory distress monitor. More specifically, the effect of using early warnings from the SOMO respiratory distress monitor to detect respiratory issues on 10 commercial pig-fattening farms in Belgium is evaluated.

Materials and methods

Farm information

The analysis in this study is based on information gathered from 10 fattening pig farms located in Flanders, Belgium, that participated in a demonstration project funded by the European Fund for Rural Development (PDPO) and the Flemish Government, Department of Agriculture and Fisheries, section Education. The goal of the project was to demonstrate the SOMO respiratory distress monitor on existing commercial pig farms in Belgium and to analyse the perception of the farmers.

The farmers were selected based on a number of criteria.

- There must be enough variation in production results and the respiratory pig health status between the farms;
- Farmers must be interested in new sensor technologies;
- Farmers and their vets must be willing to attend information meetings and workshops and participate in public discussions;
- Farmers must be willing to report on their experience with the use of the technology;
- Farmers must be willing to allow visitors in their farm within the limits of the sanitary regulations.

At the start of the project, farmers and their vets were trained to use the technology and they were informed about the project goals.

Sound recording and processing

In each farm, sound was recorded and processed using the Pig Cough Monitor (PCM) which is a commercial variant of the SoundTalks SOMO respiratory distress monitor (Figure 1). The number of pigs per compartment varied between 100 and 600. Sound recordings were taken continuously and automatically during five complete fattening periods over two years. Each compartment was equipped with one or two microphones, depending on the total number of pigs. With a specially designed algorithm, the SOMO calculates a Respiratory Distress Index (RDI) which represents the status of the respiratory system (coughing) of the pigs in the compartment.

Figure 1. SoundTalks SOMO respiratory distress monitor

The evolution of the respiratory distress index (number of coughs) measured by the SOMO devices, including the time points of the automated warnings generated by the build-in algorithm are presented to the farmer in a cloud solution and visualisation tool. Farmers received automated alerts by SMS. The system allows a continuous monitoring of the respiratory health status with the final goal to treat animals at the right moment to improve their health status, resulting in a reduction of the use of antibiotics. In earlier studies it was proven that the system detects respiratory problems two to 12 days earlier than the farmer does (Hemerijck *et al.*, 2015).

Results and discussion

Results SOMO

An example of the output of the SOMO in one of the farms is presented in Figure 2. The upper line shows the number of animals in the compartment over 2.3 fattening periods (left axis). The area shows the evolution of the Respiratory Distress Index (RDI) representing the number of coughs (right axis). The black marks (◊) indicate the moments of the alerts that were generated by the system. These alerts were automatically calculated with a patented Statistical Process Control algorithm using the history and the variation of the RDI of that specific batch.

Figure 2. Example of the evolution of the Respiratory Distress Index of one of the demonstration farms

In this particular farm, during the first round (December 2017 – April 2018) the pigs were suffering from Porcine Reproductive and Respiratory Syndrome (PRRS), and after vaccination in the second round, the cough levels were significantly lower, but an outbreak of Actinobacillis Pleuropneumonia (App) occurred at end of June 2018. Alerts were automatically generated to inform the farmer about the optimal moment to treat his animals.

Responses from farmers

Farmers were asked to answer seven multiple choice questions on-line, each time they received an alert from the SOMO system. The goal was to evaluate the experience of the users and to get a better insight in the way they treated their animals during the alert situations. The questions were:

- Do you confirm coughing of pigs in the compartment?
- Did you notice yourself any coughing in the compartment before you received an alert from the system?
- Did you use any medication against respiratory diseases, and if yes, at what moment?
- How many pigs are coughing in the compartment?
- How severe is the coughing?
- What is the general health status of the pigs?
- Do you have other remarks about the alerts given by the system?

In total, 72 replies on alert situations were given by the 10 farmers that participated in the demonstration project.

On question 1, in 74% of the cases, the farmers confirmed coughing in the compartment at the moment of the alarm. In 26% of the cases, no coughing was noticed or the number of coughs was to their opinion very low. This, of course, does not mean that the pigs didn't cough at moments when the farmer was not in the barn. Previous studies showed that coughing often occurs during night periods (Hemeryck *et al.,* 2015), or at other moments when farmers are not present in the pig house. In practice, farmers spend less than 10 minutes checking all animals in a compartment during their daily inspection rounds.

Regarding question 2, in 46% of the cases, the farmers already noticed coughing before they received an alert from the SOMO system, while in 52% of the cases, farmers were not aware of any coughing. This confirms that coughs are often not detected by a farmer and that 24 h / 7 d monitoring is useful for early detection of respiratory diseases. Otherwise, it is also possible that there was no significant amount of coughing of animals in the compartment, which is confirmed by the answer on question 5, where farmers scored 46% of the coughings as mild. In 3% of the cases, farmers noticed coughing before the alert was given based on the evolution in the graphs during the previous days in the SOMO visualisation tool.

About the use of medication in question 3, in 72% of the cases no medication was used before the alert was given, while in 11% of the cases medication was already used. In 17% of the cases, medication was applied as a result of the alert.

The number of pigs that were coughing during an alert was mainly (40% of cases) less than 50% or only some individuals (39%). In the second case, individual treatments were mainly used.

In the question 5, the type of cough was scored, with 26% no coughing (in accordance with question 1), 46% mild coughing, 24% average coughing and 4% heavy coughing.

The general health status of the pigs was in 86% of the cases normal and in only 14% there was a reduction of feed intake, lower activity or body condition. In some extreme cases pigs died from lung lesions.

A summary of the answers from the farmers is presented in Figure 3.

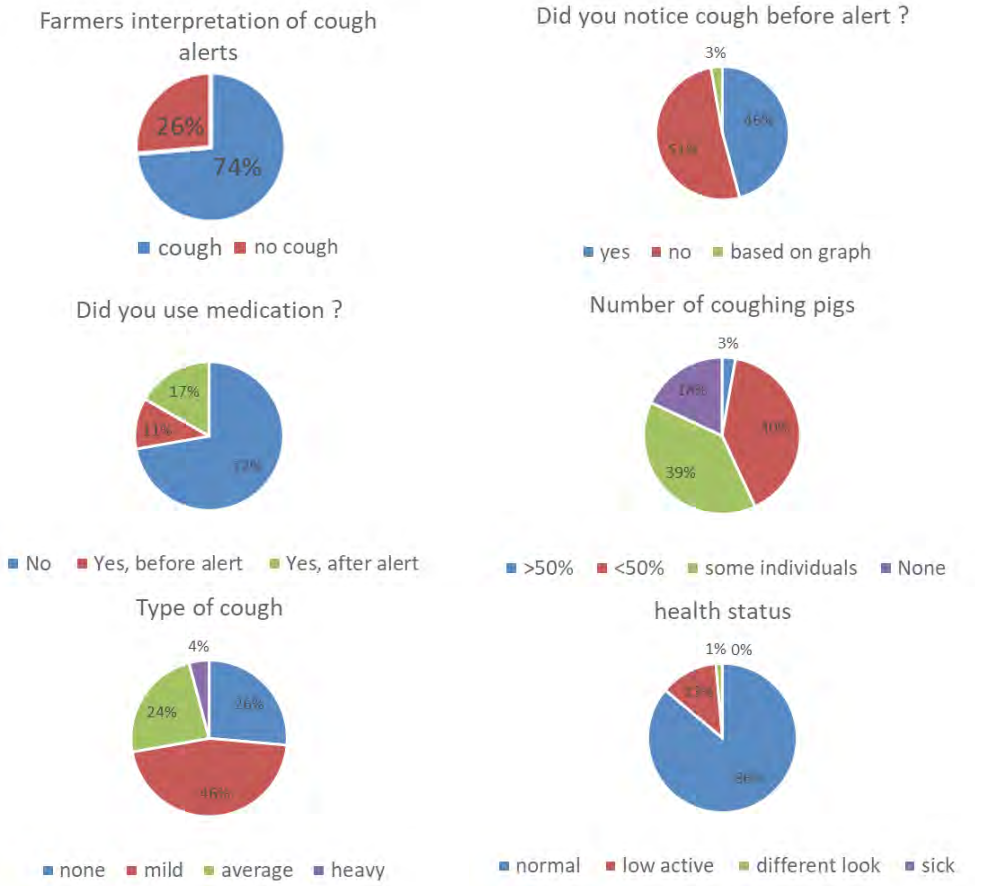

Figure 3. Results of farmers feedback of cough alarms

Discussion

Although user feedback is a very powerful tool for building better products and early warnings, we have to be careful with interpreting the results. First of all the interpretation can be very subjective and different for each user. The time pig farmers spend with their animals is relative small (on average 10 minutes per compartment per day) and consequently it cannot be seen as a gold standard for a continuous monitoring system. In the project, blood samples were taken from some animals, but because of the high costs involved, sample numbers were not sufficient to show any clear relation with the RDI.

On the other hand, feedback from farmers and their vets was helpful for optimising the visualisation tool and a better definition of the algorithm settings. In most cases, the veterinary treatment of the animals was based on the RDI data, and in general, animals were treated earlier, resulting in a lower use of antibiotics.

The base level of the RDI is farm specific and absolute values cannot be used as alarm levels. Using statistical process control helped to overcome the problem, but in future, farm history of RDI levels can help to improve the early warning software and make it farm specific.

Conclusions

In a demonstration project in Flanders (Belgium), the SOMO Respiratory Distress Monitor of SoundTalks, was installed in 10 commercial fattening pig houses showing an automatic alarm when respiratory problems occurred. In total, about 200 fattening periods were followed up. The warnings of the SOMO-system were analysed against the observations of the farmer. In total, 72 cough alerts occurred on which farmers gave feedback.

In most cases (74%) the alert situation was confirmed by the farmers inspection, and in 17% of the cases farmers started a medical treatment based on the alerts. At the time of the alert the number of sick animals was still low and the behaviour (activity, feed intake) of the animals still normal in most cases (86%). It was confirmed by the farmers that the use of the SOMO system helped to reduce the amount of medication, because treatments were done in an early stage of infection.

Acknowledgements

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References

Berckmans, D. (2004). Automatic On-line Monitoring of Animals by Precision Livestock Farming. *In: ISAH conference "Animal production in Europe: The way forward in a changing world*, October 2004, Saint-Malo, France, 1, pp.27–31.

Chung, Y., S. Oh, J. Lee, D. Park, H.-H. Chang, S. Kim (2013). Detection and Recognition of Pig Wasting Diseases Using Sound Data in Audio Surveillance Systems. *Sensors,* 13(10): 12929–12942.

Ferrari, Sara, Mitchell Silva, Marcella Guarino, and Daniel Berckmans (2008). Analysis of Cough Sounds for Diagnosis of Respiratory Infections in Intensive Pig Farming. *Transaction of the ASABE* 51(3): 1051–55.

Hemeryck, M., D. Berckmans (2015). Pig Cough Monitoring in the EU-PLF Project: First Results. *Precision Livestock Farming Applications*, pp.199 – 208.

Vandermeulen, J., Decré, W., Berckmans, D., Exadaktylos, V., Bahr, C., and Berckmans, D. (2013). The Pig Cough Monitor: From Research Topic to Commercial Product. *In Proceedings of Precision Livestock Farming* 2013 Leuven, pp.17–23.

Van Hirtum, A., J.–M. Aerts, D. Berckmans, B. Moreaux, P. Gustin (1999). On–line cough recognizer system. *J. Acoust. Soc. America,* 106(4:2): 2191–2194.

Effect of environmental enrichment on the surface temperature, skin lesion score and behaviour during transportation of pigs

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Abstract

The aim of the study was to evaluate the environmental enrichment effect during transport of pigs on the surface temperature (ST), skin lesion score (LE) and behaviour, considering as an enrichment the creation of a familiar environment between the housing facilities and the transport vehicle. Two experiments were conducted: the first during transport of the Piglets Production Unit to the nursery and the second during transportation of animals from the Finisher Unit to the slaughterhouse. The animals (n = 250, Exp I and n = 120, Exp II) were distributed in a completely randomised design to five treatments: T1 - control without environmental enrichment; T2 - use of enrichment objects in the truck; T3 - familiar environment using lavender aroma; T4 - familiar environment using music; T5 - familiar environment using truck noise. Treatments were applied at the housing facility five days before transportation and during transportation. The ST of the skin was evaluated by an infrared thermal imager and the skin LE by observation (after transport). The ST of the skin after transport from the Piglets Production Unit to the nursery and from the Finisher Unit to the slaughterhouse was smaller for swine that received the treatment with music. There was no effect of treatments on skin LE in both experiments. Piglets from experiment I exposed to music, had less agonistic behaviour compared to the other treatments. Creating a familiar environment for pigs through the use of music can be promising in improving animal welfare during transport.

Keywords: thermography, welfare, surface temperature, music therapy, swine

Introduction

Transport is a common practice in pig farming and can occur more than once throughout the production cycle or its reproductive life (Faucitano & Goumon, 2018). It is considered a critical moment in the life of the animal, with serious implications for its welfare, since they are exposed to numerous potentially stressful factors such as climate, management by unknown people, batch mixing, transport stock density, new odors, sounds and duration of transportation, among others (Pereira *et al.*, 2015).

Farm conditions are considered important sources of variation in the ease of handling pigs for transport. During the productive life, swine are normally kept in the same bay in a sterile environment, with little stimulation and usually without any environmental enrichment, resulting in animals that present a high degree of reactivity to new stimuli, less developed social behaviour or increased fear (Rocha *et al.*, 2016). In contrast, Tönepöhl *et al.* (2012) identified that animals raised in an enriched environment are easier to handle during shipment and less responsive to transport stress, fighting less when mixed.

Research has shown satisfactory results with the use of environmental enrichment during the breeding of pigs in several stages (de Jonge *et al.*, 2008). However, few alternatives are discussed to reduce transport stress, except for climatic conditions and density.

The use of environmental enrichment in transport can have beneficial effects on the

physical and psychological welfare of swine, significantly improving this stage, considered as one of the most stressful for animals. Since the fear of the unknown is one of the factors with great impact in the transport, it is presumed that the creation of an environment previously experienced, such as the reproduction of sounds with which animals are familiar in their breeding environment, may be a good alternative to reduce neophobic responses and stress. Unknown sounds for animals such as truck engines and vehicles, in general, can be very stressful, and subjecting the pigs to these sounds before transport to make them familiar can be a good strategy for fear reduction.

To increase understanding on the subject, a broad approach is needed, including studies of animal physiology and behaviour. The objective of this study was to evaluate the effects of environmental enrichment for pigs during transport in different stages of the production cycle, considering as enrichment the creation of a familiar environment during transportation.

Material and methods

Experimental data

Two experiments were conducted in the state of Mato Grosso do Sul, Brazil. The first, during transportation of the Piglets Production Unit to the nursery, and the second during transportation of animals from the Finisher Unit to the slaughterhouse.

The animals (Experiment I: 120 hybrid females DanBred, weaned with an average of 28 days old; and Experiment II: 120 hybrid females DanBred, with an average weight of 120 kg), were distributed in five treatments: T1 - control treatment without environmental enrichment; T2 - use of enrichment objects made using hydraulic PVC pipe, with holes in the sides on which were attached non-toxic plastic hoses (Figure 1), allowing pigs develop exploratory activity. The objects were fixed to the sides of the truck compartments, with plastic clamps at the height of the eyes of the animals. These objects were used only in the transport truck, not being offered prior to transportation; T3 - the creation of a familiar environment using a lavender aroma in the pen five days before transportation and during it. Lavender odour-filled sachets were made and distributed inside the creep (Experiment I), in the pens (Experiment II) and in the truck compartments (Experiment I and II); T4 creating a familiar environment with the use of music. It used a varied repertoire of songs played by speakers at 60 decibels maximum sound pressure, distributed in the maternity room (Experiment I) and fattening room (Experiment II), uninterrupted for eight hours per day for the five-day pre-transport period. The same playlist was used during transportation of the animals, in a speaker placed between the compartments of the truck; T5 - the creation of a familiar environment using vehicle sounds. Recordings of running vehicle sounds were used, which were played by speakers at the maximum sound pressure of 60 decibels, arranged throughout the maternity (Experiment I) and fattening rooms (Experiment II), two hours a day, for the five-day pre-transport period. During transportation, the sound of the truck itself was considered. This treatment aimed to familiarise the animals with the noises produced by the truck and vehicles on the highways, aiming to reduce the stress of this unknown factor.

The animals from each treatment were housed in separate maternity and fattening rooms so that one treatment did not influence the other. The same care was taken during the animal's transportation. In experiment I the distance travelled was 60 km, with a duration of 70 minutes while in experiment II the distance travelled was approximately 32 km, during 60 minutes.

Figure 1. Object of enrichment used in the piglet's transportation truck from the Pig Production Unit to the nursery (Treatment 2)

Score of skin lesions

Determined through visual evaluation, according to the adapted methodology proposed by Brown *et al.* (2009), the number of lesions found throughout the body of 30 animals per treatment at the Piglet Production Unit and 15 animals by treatment of the fattening unit, chosen at random were counted. The lesion scores were classified as 0 - absent (absence of lesions), 1 - mild (one to five lesions), 2 - moderate (six to 11 lesions) and 3 - severe (12 lesions or more). Only recent lesions were considered, with no signs of healing.

Surface temperature

Pre-transport skin temperature measurements (24 hours prior to animal's shipment) and post-transport (immediately after unloading of animals in the nursery and slaughterhouse) were performed. The thermographic images were recorded in 24 animals per treatment, randomly selected. The surface temperature of the animals was evaluated using Termovisor Infrared Reporter equipment and by specific software for this equipment. The colour spectrum reading was converted to surface temperature. The emissivity coefficient used was 0.96 for the entire body surface of the animal. The mean surface temperature and standard deviation of the body area were calculated using the temperature of 30 spots selected to represent the overall body surface of the animals (Figure 2).

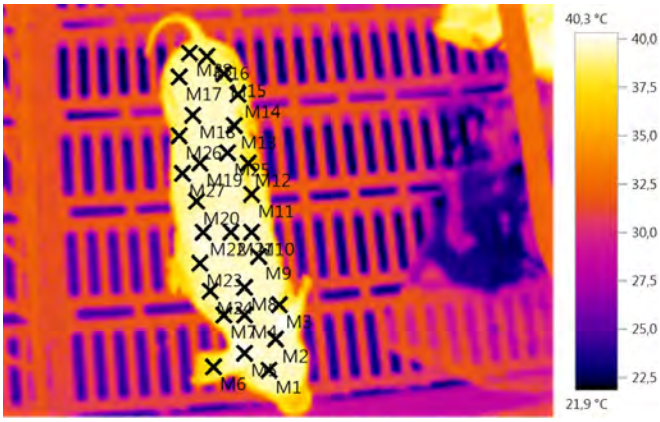

Figure 2. Thermographic image of the piglet before transportation. Points selected for determination of mean surface temperature

Behavioural evaluation during transport

For behavioral evaluation, a monitoring system with video cameras (Action Go Pr Sport Ultra 4K Full) was used to record uninterrupted behaviour and posture of the pigs during transportation. The cameras were installed in each compartment of the truck in order to allow the visualisation of all the animals during each treatment. The videos were watched and the behaviours recorded according to an ethogram elaborated and adapted from Sutherland *et al.* (2009).

To make the frequency histogram of behavioural activities, the images were visualised through the Windows Media Player program and every five minutes the recording was paused. All the animals present in the truck compartment were evaluated, and the data were recorded in a spreadsheet showing the number of animals and their respective activities. The behaviour was analysed individually and each animal considered an experimental unit. For the behavioral analysis, 50 animals per treatment of Experiment I and 12 animals per treatment of Experiment II were observed.

Statistical Analysis

In all analyses, the animal was used as an experimental unit. The behavioural data were analysed as mixed generalised linear models, considering as fixed effects the different treatments (control, aroma, music, object, vehicle sounds) and time as a random effect. In this approach, a Poisson distribution was also considered when the variables were derived from the sum of the behaviour, and binary distribution for the lesion score data using the SAS GLIMMIX procedure (version 9.4; SAS Institute Inc., Cary, NC). For the body temperature data, no adjustments were necessary for the distribution of the data. When significant, the means between variables were compared using the Tukey test. Significance was assigned when $P < 0.05$.

Results and discussion

Score of skin lesions

There was no effect of the treatments on the skin lesion score of piglets after transportation from the Piglet Production Unit to the nursery ($P > 0.05$). In the same way, there was no effect of treatments on the skin lesion score of pigs after transport from the Fattening Unit to the slaughterhouse ($P > 0.05$) (Figure 3). However, for this category, no score 0 was observed, i.e. all animals evaluated had some type of skin lesion even before transport, distributed among scores one to three. The effects of hanging objects and substrate (shavings) as enrichment strategies for piglets were investigated during lactation up to ten days after weaning on the skin lesion score, one day before weaning and the first two days after weaning. Yang *et al.* (2018) concluded that enrichment did not influence the number of lesions before and after weaning. Other studies, however, indicate the benefits of using environmental enrichment in reducing the incidence of skin lesions. According to Tönepöhl *et al.* (2012), the scores of pig's lesions in commercial conditions housed in a sterile environment were higher than in pigs housed in enriched environments. The authors suggest that the relative absence of stimuli for the development of species-typical behaviours, such as exploration and foraging, alternately promotes more frequent interactions with their co-specific species.

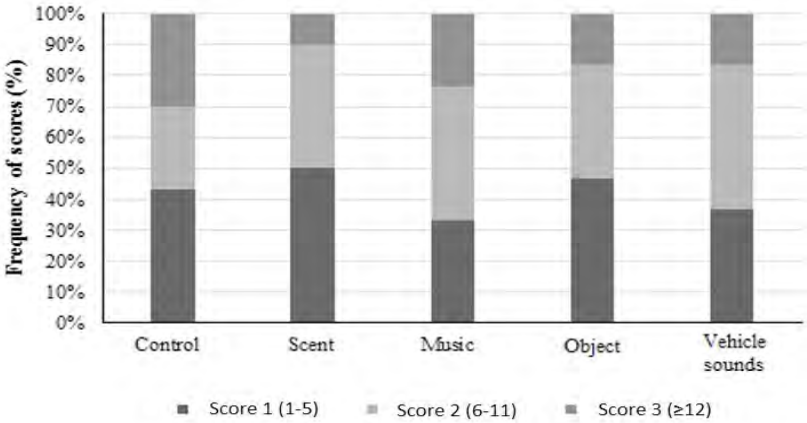

Figure 3. The frequency of post-transport skin lesion scores of animals from Fattening Unit to the slaughterhouse (Experiment II)

Evaluating the effects of transport time and sex on the number of skin lesions in pigs, Mota-Rojas *et al.* (2006) observed that males had a higher incidence of hematomas in the skin, regardless of the duration of transport. Skin lesions are usually the result of transport struggles between pigs and they occur to a greater extent between males than between females (Geverink *et al.*, 1996). In the present study, female piglets were used and there was no mixing of lots during shipment, which favoured the non-occurrence of fights during transportation. Hwang *et al.* (2016) affirm that the smaller number of lesions observed in a lot may suggest familiarity with the other animals of the pen, reducing the severity of the conflicts.

Temperature

The skin surface temperature of the piglets was similar between all treatments before transport ($P > 0.05$), being lower after transportation to the animals of the treatment with music (Table 1). The measured temperatures are within the conditions of thermal comfort, before and after transportation, according to Manno *et al.* (2005).

Temperature is a factor that rules the intensity of stress an animal suffers during transportation. The ideal thermal comfort zone varies as the piglets age. The thermal comfort zone for weaned piglets (about 7 kg) is within the dry bulb temperature range of 20–22 °C and 60–70% relative humidity when the wind speed is close to 0.5 m s^{-1} (Tolon *et al.*, 2016) and temperature can fluctuate rapidly during transport in not air-conditioned vehicles (Tarrant & Grandin, 2000).

No effect of treatments ($P > 0.05$) on the surface temperature of the pig's skin was observed before transport of the Finisher Unit to the slaughterhouse (Table 2). However, after transportation, pigs from the control and music treatments showed lower skin surface temperature ($P < 0.05$). The total reduction of the surface temperature after the transport can be related to the fact that the transport occurred in the night period, favoring convection heat exchanges, in detriment to the heat gain by radiation. The use of sensory stimuli such as sounds and aroma, seeking calm down and make environments familiar to animals, can be presented as enriching sources that help on the alleviation of stress and contribute to the positive welfare (Maia *et al.*, 2013).

Table 1. Surface temperature (ST, °C) of the skin before and after transport of the piglets from the Piglets Production Unit to the nursery (Experiment I)

	Treatment						
	Control	**Lavender aroma**	**Music**	**Object**	**V.S.**	**SEM**	**P-Value**
Pre-transport							
ST, °C	34.37a	33.88a	33.34a	34.16a	34.51a	0.439	0.3789
Post-transport							
ST, °C	32.85ab	34.74a	31.95b	34.23a	33.34ab	0.656	0.0225

V.S. = Vehicle sounds; SEM = Standard error of the mean; [a, b, c] Means with different letters in the same row differ among themselves by the Tukey test at 5% significance

Table 2. Surface temperature (ST, °C) of the skin before and after transport of the pigs from the fattening unit to the slaughterhouse (Experiment II)

	Treatment						
	Control	**Lavender aroma**	**Music**	**Object**	**V.S.**	**SEM**	**P-Value**
Pre-transport							
ST, °C	34.67a	34.57a	34.51a	34.42a	34.53a	0.1533	0.8252
Post-transport							
ST, °C	29.70b	31.66a	28.79b	30.93a	31.21a	0.3051	<0.001

V.S. = Vehicle sounds; SEM = Standard error of the mean; [a, b, c] Means with different letters in the same row differ among themselves by the Tukey test at 5% significance

Behaviour during transport

Piglets submitted to music enrichment before and during transport to the nursery had a lower frequency of agonistic behaviour during transport than the animals from the other treatments (Table 3). Similarly, results obtained by De Jonge *et al.* (2008) point out that piglets exposed to music before weaning presented increased play behaviour in the daycare phase and reduced aggressive behaviours, constituting a positive indicator of well-being.

Table 3. Behavioural frequency (%) of piglets during transport from UPL to nursery (Experiment I)

	Treatment						
	Control	**Lavender aroma**	**Music**	**Object[1]**	**V.S.**	**SEM**	**P-value**
Activity %							
Agonistic behaviour	0,31a	1,38a	0b	1,23a	0,31a	0,3872	0,0365
Resting	17,38a	3,23bc	12,46ab	2,62c	14,46a	2,964	0,0011
Standing	35,38b	55,23a	37,85b	45,23ab	36,92b	3,5714	0,0012
Moving around	5,69ab	8,77a	4,62b	8,31ab	8,77a	0,9982	0,0093
Jumping over another	6,62b	13,85a	8,92b	13,85a	8,92b	1,4306	<0,001
Seated	34,62a	17,54b	36,15a	26,77ab	30,62a	2,8732	0,0002

V.S = Vehicle sounds, SEM = Standard error of the mean, 1: Interactivity activity with the object corresponded to 1.99% of the time. [a, b, c]: means with different letters in the same row differ among themselves by the Tukey test at 5% significance

In experiment II, during transportation of the finishing unit to the slaughterhouse, pigs exposed to the sounds of vehicles five days before slaughtering and during transportation spent more time resting, and consequently less time standing in relation to the animals of the other treatments, which did not differ among them (Table 4).

Table 4. Behavioural frequency (%) of piglets during transport from finishing unit to the slaughterhouse (Experiment II)

	Treatment						
	Control	**Lavender aroma**	**Music**	**Object[1]**	**V.S.**	**SEM**	**P-value**
Activity %							
Resting	35,26b	35,26b	28,21b	32,69b	63,46a	10,933	0,0003
Standing	30,77a	30,77a	41,67a	39,10a	9,62b	9,585	< 0,001
Moving around	0	0	0,64	0	0	0,573	0,4168
Seated	33,97	33,97	29,49	26,92	26,92	8,427	0,5749

V.S = Vehicle sounds, SEM = Standard error of the mean, 1: Interactivity activity with the object corresponded to 1.29% of the time. [a, b, c]: means with different letters in the same row differ among themselves by the Tukey test at 5% significance

Agonistic behaviours and jumping on other pigs were not observed at this stage. Familiarity with the noises present during transport may have attenuated the stress of the animals, which got used to the environment more quickly and soon put themselves in a rest position. However, this fact was not observed during the transportation of the piglets from the UPL to the nursery. According to Sutherland *et al.* (2014), the weaning stress is so severe for piglets that in the transport of up to six hours, no additive effects are observed.

Conclusions

The use of sound stimuli such as music in order to become more familiar with distinct environments to pigs is presented as a promising tool for reducing fights during transport, and thus improved welfare in this critical phase. The effects of this kind of enrichment are most pronounced in the early stages of life.

More research should be conducted evaluating longer periods of familiarisation with the enriching, as well as long transport periods. New strategies for the use of enrichment objects can be evaluated for greater effects.

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References

Brown, J.A., Dewey, C., Delange, C.F., Mandell, I.B., Purslow, P.P., Robinson, J.A., & Widowski, T.M. (2009). Reliability of temperament tests on finishing pigs in group-housing and comparison to social tests. *Applied Animal Behaviour Science*, 118(1-2): 28–35.

de Jonge, F.H., Boleij, H., Baars, A.M., Dudink, S., & Spruijt, B.M. (2008). Music during play-time: Using context conditioning as a tool to improve welfare in piglets. *Applied Animal Behaviour Science*, 115(3-4), 138–148.

Faucitano, L., & Goumon, S. (2018). Transport of pigs to slaughter and associated handling. In *Advances in Pig Welfare* Woodhead Publishing 261–293.

Geverink, N.A., Engel, B., Lambooij, E., & Wiegant, V.M. (1996). Observations on behaviour and skin damage of slaughter pigs and treatment during lairage. *Applied Animal Behaviour Science*, 50(1): 1–13.

Hwang, H.S., Lee, J.K., Eom, T.K., Son, S.H., Hong, J.K., Kim, K.H., & Rhim, S.J. (2016). Behavioral characteristics of weaned piglets mixed in different groups. *Asian-Australasian Journal of Animal Sciences*, 29(7): 1060.

Maia, D.A., A.P., Sarubbi, J., Medeiros, B.B.L., & de Moura, D.J. (2013). Environmental enrichment as positive welfare of pigs: a review. *Revista Eletronica em Gestão, Educação e Tecnologia Ambiental*, 14(14): 2862–2877.

Manno, M.C., Oliveira, R.F.M.D., Donzele, J.L., Ferreira, A.S., Oliveira, W.P.D., Lima, K.R.D.S., & Vaz, R.G.M.V. (2005). Effect of thermal environment on performance of growing pigs from 15–30 kg. *Revista Brasileira de Zootecnia*, 34(6): 1963–1970.

Mota-Rojas, D., Becerril, M., Lemus, C., Sánchez, P., González, M., Olmos, S.A., ... & Alonso-Spilsbury, M. (2006). Effects of mid-summer transport duration on pre-and post-slaughter performance and pork quality in Mexico. *Meat Science*, 73(3): 404–412.

Pereira, T.L., Corassa, A., Komiyama, C.M., Araújo, C.V., & Kataoka, A. (2015). The effect of transport density and gender on stress indicators and carcass and meat quality in pigs. *Spanish Journal of Agricultural Research*, 13(3): 0606.

Rocha, L.M., Velarde, A., Dalmau, A., Saucier, L., & Faucitano, L. (2016). Can the monitoring of animal welfare parameters predict pork meat quality variation through the supply chain (from farm to slaughter)?. *Journal of Animal Science*, 94(1): 359–376.

Sutherland, M.A., Krebs, N., Smith, J.S., Dailey, J.W., Carroll, J.A., & McGlone, J.J. (2009). The effect of three space allowances on the physiology and behavior of weaned pigs during transportation. *Livestock Science*, 126(1-3), 183–188.

Sutherland, M., Backus, B., & McGlone, J. (2014). Effects of transport at weaning on the behavior, physiology and performance of pigs. *Animals*, 4(4): 657–669.

Tarrant, V., & Grandin, T. (2000). Cattle transport. In: Grandin, T. (Ed.) *Livestock handling and transport*, 2nd *edition*. CAB International, Wallingford, UK, pp. 151–173.

Tolon, Y.B., Nääs, I.A., Baracho, M.D.S., & Moura, D.J. (2016). Housing thermal comfort zone for weaned to growing pigs. In *2016 ASABE Annual International Meeting* (p. 1). American Society of Agricultural and Biological Engineers.

Tönepöhl, B., Appel, A.K., Welp, S., Voß, B., von Borstel, U.K., & Gauly, M. (2012). Effect of marginal environmental and social enrichment during rearing on pigs' reactions to novelty, conspecifics and handling. *Applied Animal Behaviour Science*, 140(3-4), 137–145.

Yang, C.H., Ko, H.L., Salazar, L.C., Llonch, L., Manteca, X., Camerlink, I., & Llonch, P. (2018). Pre-weaning environmental enrichment increases piglets' object play behaviour on a large scale commercial pig farm. *Applied Animal Behaviour Science*, 202, 7–12.

Session 8

Monitoring Animal Health and Behaviour

Assessing feasibility of using depth images to acquire body condition score of sows

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Abstract

Observation, control and maintenance of physical condition of sows in acceptable levels is critical to maintain animal welfare and production standards. Early recognition of animals that present atypical physical condition is important to prevent production losses. Currently, classification of body condition is done by subjective methods, thus is dependent on the opinion of the manager, which can generate differences between ratings. As alternatives to these subjective methods of classification, various methods have been proposed to obtain a more objective measure. Knauer & Baitinger (2015) developed a calliper that quantifies the angularity from the spinous process to the transverse process of a sow's back and concluded that this instrument can be used as a tool to standardise this classification. Another way to standardise this measurement would be to automate the process by analysing images generated by depth cameras. The present work aimed to obtain sow's body condition score (BCS) using a commercially available depth camera. This was done by correlating the scores obtained with a BCS calliper (scores ranging from 1 to 29) with the sow's body widths acquired from depth images. A multiple linear regression was performed with an R^2 of 0.61, a standard error of 1.36, and average absolute error of 8.01% (1.05 units). These errors may be associated with poor repeatability (human error) and/or the measurement calliper. It is considered that there is a need for a reliable gold standard and depth images analysis could be a possible option.

Keywords: image analysis, automation, depth cameras

Introduction

The observation, control and maintenance of the physical condition of sows in acceptable levels is critical to maintain the animal welfare and production in appropriate standards. The animal welfare assessment protocol for pigs, Welfare Quality® (WELFARE QUALITY®, 2009), states that good feeding, one of the principles of the animal welfare, is composed of two criteria: absence of prolonged hunger and absence of prolonged thirst. It is proposed to evaluate the first criterion on sows by measuring the body condition of the animals. This is suggested to be done in a subjective method, visually and by touch, classifying the body condition in three levels: Level 0 (sow in good condition, with well-developed muscles on the bone), Level 1 (thin sow, with bones easily felt; or sow visually obese) and Level 2 (very thin sow, with the hips and backbone prominent).

It is known that, during pregnancy, each sow should receive a different amount of food according to its body condition. Bigger, older or skinnier sows should receive higher amounts of food to meet their nutritional needs. Underweight animals present nutritional deficiency, fewer piglets born per litter, and those that are born, can present also nutritional deficiencies and smaller body mass (Eissen *et al.,* 2000). Overweight sows are usually larger than the space provided in the pen, which leads to stress for the animal and may cause piglets' crushing. In addition, these sows have an abnormal development of mammary

glands, reducing the amount of milk produced during lactation. Sows that are obese during pregnancy tend to reduce the amount of food ingested during lactation, which also reduces the amount of milk produced (Eissen *et al.,* 2000). All these factors result in economic losses.

Therefore, the early recognition of animals that present physical condition outside the standards is important to prevent production losses. Some authors have been using ratings like those proposed by the Welfare Quality® to assess body condition of sows over the years (Esbenshade *et al.,* 1986; Patience & Thacker, 1989; Charette *et al.,* 1996; Maes *et al.,* 2004; Knauer *et al.,* 2007; Knauer *et al.,* 2012; Salak-Johnson *et al.,* 2014; Knauer & Batinger, 2015). As alternatives, various methods have been proposed to obtain a more objective measure.

To reduce the errors with the body condition scoring, one should try to reduce the variation generated by the classification done by different managers. A way of doing that was proposed by Knauer & Baitinger (2015), who developed a calliper that quantifies the angularity from the spinous process to the transverse process of a sow's back and concluded that this instrument can be used as a tool to standardise this classification. Another way to standardise this measurement would be to automate the process by analysing images generated by depth cameras. This method was used for dairy cows (Kuzuhara *et al.,* 2015), obtaining a correlation of 74% between the predicted and actual body condition score. This can indicate the possibility of using this method for sows.

The present work aims to obtain the body condition score of sows using a commercially available depth camera.

Material and methods

The experiment was conducted in a gestating building of the U.S. Meat Animal Research Center, from the Agriculture Research Service-ARS of United States Department of Agriculture – USDA (-98.13° W, 42.52° N). Animal digital and depth images were collected on a population of sows at four parities. All animal procedures were performed in compliance with federal and institutional regulations regarding proper animal care practices (FASS, 2010).

Preliminary Study

A preliminary study was conducted to test the calliper proposed by Knauer & Baitinger (2015) and the feasibility of using depth images to obtain a correlation with the values of body condition score (BCS). For that, depth images (Figure 1) of a paper cylinder were acquired and the BCS was obtained with the calliper. The size of the paper cylinder was set to obtain a BCS range from seven to 21. The cylinder was selected on the image by a depth threshold and its width was acquired in pixels and, then, transformed to cm using Equation 1.

Animal Specifics

One-hundred and seven sows at four different parities (1, 2, 3, and 4), weighing approximately between 150 and 250 kg, from a rotational Landrace and Yorkshire cross were sampled. The animals were allocated in a gestating building. Animals were sampled at two different time-points: on the day of moving to the farrowing building and on the day of moving from the farrowing building. The first group received a restricted diet and *ad libitum* water and were housed in a group-pen; while the second group had *ad libitum* access to both feed and water and were housed in individual crates. Diets were a mix of corn and soybean meal formulated to meet or exceed National Research Council recommendations (NRC, 2012).

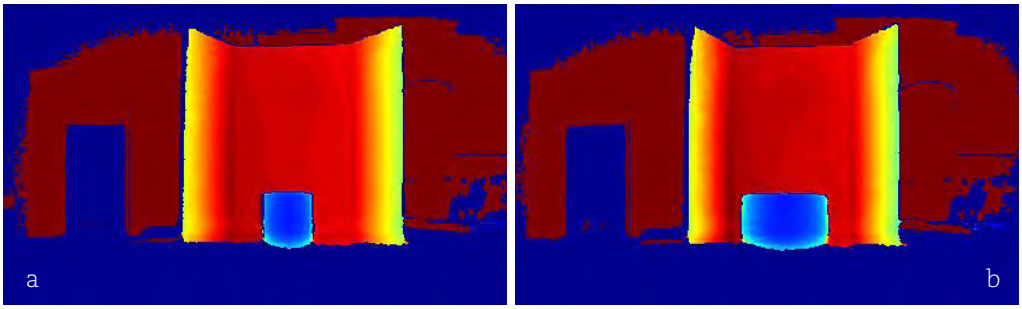

Figure 1. Depth images of paper cylinder (centre of image) with a BCS of 7 (a) and 21 (b)

$$l_{cm} = l_{px} / \frac{l_{px}}{(3.669 \times Z_m^{-0.915})} \qquad (1)$$

where l_{cm} is the length, in cm; l_{px} is the length, in pixels; and Z is the distance from the camera to the object being analysed, in meters.

Data Acquisition

Microsoft® Kinect Studio program was used to acquire both digital RGB colour and depth videos from a commercially available depth camera (Microsoft Kinect® v.2). The program was deployed on a Windows®-based computer for data collection. A camera was positioned above the hallway of the building mounted on the ceiling to take both dorsal colour (1,920 × 1,080 pixels per frame, Figure 2a) and depth videos (512 × 424 pixels per frame, Figure 2b) of the animals at approximately 30 frames per second.

To acquire the body condition score of animals, the calliper proposed by Knauer & Baitinger (2015) was used as standard (Figure 3).

Figure 2. Example of (a) colour and (b) depth frames acquired

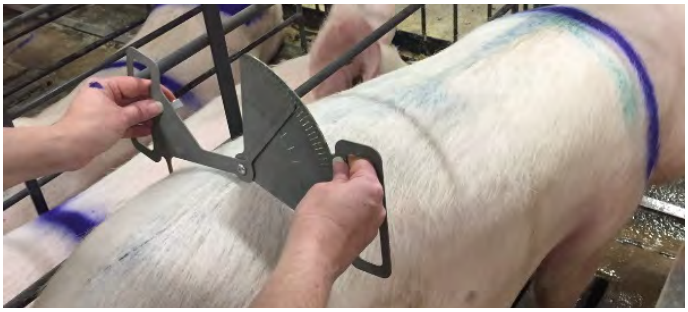

Figure 3. Body condition score acquired with calliper proposed by Knauer & Baitinger (2015)

Data Analysis

An algorithm proposed by Condotta *et al.* (2018) was used in a numerical computing software (MATLAB, version R2018a) for pre-processing the images. After that, the last rib region of the animal was selected. For that, first the smaller column on the image belonging to the back half of the animal's body was selected as being the last rib region (Figure 4a). Then, the length of the curvature at the last rib was obtained (Figure 4b). An ellipse was fitted on the animals' body and its minor axis length was acquired (Figure 5). Equation 1 was used for unit transformation (from pixels to cm).

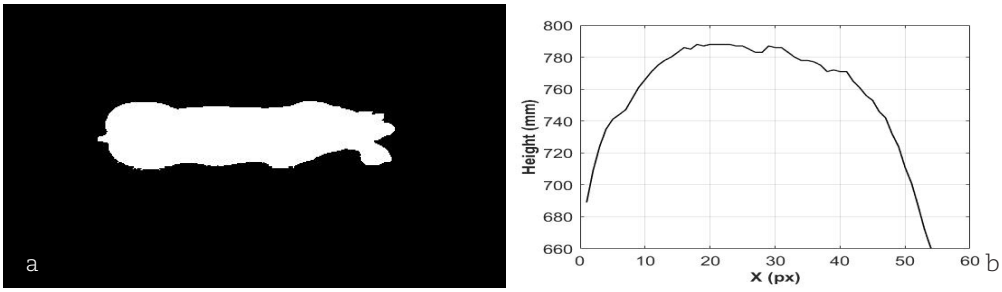

Figure 4. (a) Last rib region and (b) curvature at last rib

Figure 5. Ellipse fitted on sows' body and minor axis of ellipse acquired for a sow with a body condition score of eight (a) and for a sow with body condition score of 17 (b)

Results and discussion

The preliminary results showed a high correlation (Figure 6) between width of the paper cylinder and body condition score (BCS), with an R^2 of 0.9792 and an average absolute error of 3.2%, or 0.47 units of BCS.

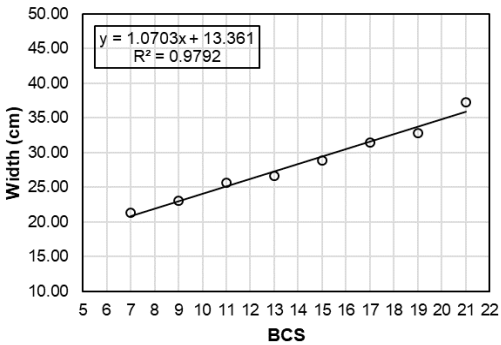

Figure 6. Width of paper cylinder, in cm, versus body condition score (BCS) obtained with calliper

Although the preliminary results showed a high correlation between width and BCS, the same did not apply to width of sows' body. Figure 7 shows the results of simple linear regressions between lengths of both minor axis of ellipse fitted on sow's body and of last rib curvature, in cm, and the body condition score (BCS) collected with the calliper. Body condition scores of the population ranged from eight to 17.5 units.

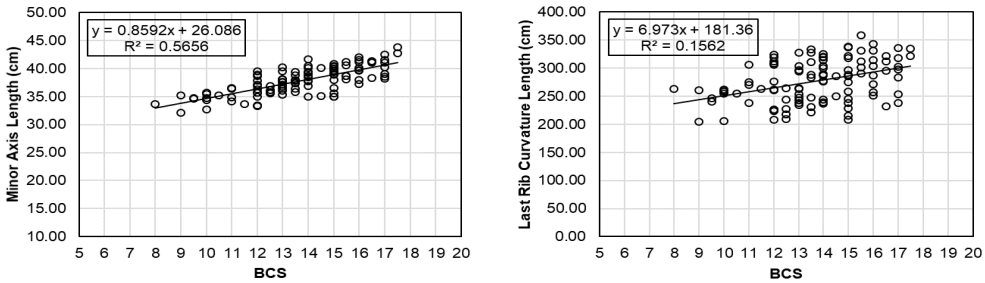

Figure 7. Lengths of minor axis of ellipse fitted on sow's body (a) and of last rib curvature (b), in cm, plotted against body condition score (BCS) collected with calliper

A multiple linear regression was performed (Equation 2) to obtain BCS using length of minor axis and length of last rib curvature as inputs. The R^2 for this regression was 0.6108, with a standard error of 1.3586 (Table 1) and average absolute error of 8.01%, or 1.05 units.

$$BCS = -13.7479 + 0.8523\ MA \times -0.0174 \times CL \qquad (2)$$

where *BCS* is the body condition score; *MA* is the length of minor axis of ellipse fitted around sow's body, in cm; and CL is the length of curvature at last rib, in cm.

Table 1. Multiple linear regression statistics

Regression statistics	
R^2	0.6108
Standard error	1.3586
Observations	107

Previous results obtained by Kuzuhara *et al.* (2015) showed an R^2 of 0.73 for a multiple linear regression predicting BCS of cows that used as inputs six geodesic lines along the back of the animal and parity. The results obtained in the present work were slightly lower, but the animal differences in anatomy should be taken in consideration and the comparison should be done with reservations.

The errors on the model could have been caused by different sources. One source could be human error, failing to consistently acquire the body condition score with the calliper due to animal's movement specially when the animals were in the group pens and had more range of movement.

Figure 8 shows the curvatures at last rib for two sows classified with a body condition score of 12. One sow was younger and pregnant (located in the group pen), while the other was an open sow located in an individual crate. It's easy to see that the curvature for both sows is different, with one animal being wider than the other. This difference

could indicate either a measurement error or that the back curvature does not correlate so well with the calliper measurements. Knauer & Baitinger (2015) found a maximum correlation between BCS and calliper measurements of 0.76, indicating that, although a less subjective measurement of BCS is much needed, we are still far from having a perfect gold standard for this variable.

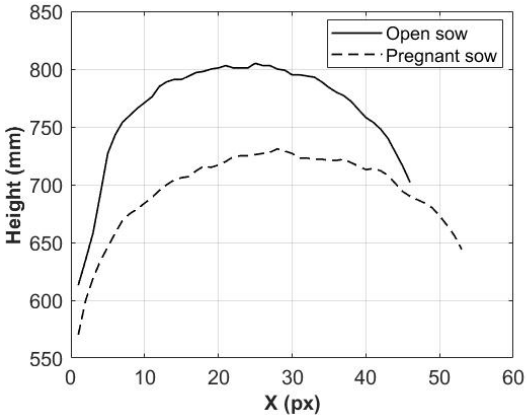

Figure 8. Curvature at last rib for two sows classified with a body condition score of 12. The shorter and wider sow (dashed line) was younger and pregnant

Next steps on this research will consider parity, back fat and mass on the model, as these variables showed correlation with body condition score in previous studies (Maes *et al.*, 2004; Charette *et al.,* 1996).

Conclusions

A multiple linear regression was performed to obtain BCS using length of minor axis and length of last rib curvature as inputs, with an R^2 of 0.6108, a standard error of 1.3586, and average absolute error of 8.01%, or 1.05 units. These errors could be correlated with both difficult on repeatability (human error) or associated with the error of the standard itself (the calliper). It is observed a need for a reliable gold standard and depth images analysis could be a possible candidate. For that, a model that uses other input variables, like parity, back fat and mass could be used for calibration purposes.

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References

Charette, R., Bigras-Poulin, M., & Martineau, G.P. (1996). Body condition evaluation in sows. *Livestock Production Science*, 46(2): 107–115.

Condotta, I.C., Brown-Brandl, T.M., Silva-Miranda, K.O., & Stinn, J.P. (2018). Evaluation of a depth sensor for mass estimation of growing and finishing pigs. *Biosystems Engineering*, 173: 11–18.

Eissen, J.J., Kanis, E., & Kemp, B. (2000). Sow factors affecting voluntary feed intake during lactation. *Livestock Production Science*, 64(2-3): 147–165.

Esbenshade, K.L., Britt, J.H., Armstrong, J.D., Toelle, V.D., & Stanislaw, C.M. (1986). Body condition of sows across parities and relationship to reproductive performance. *Journal of animal science,* 62(5): 1187–1193.

Kuzuhara, Y., Kawamura, K., Yoshitoshi, R., Tamaki, T., Sugai, S., Ikegami, M., ... & Yasuda, T. (2015). A preliminarily study for predicting body weight and milk properties in lactating Holstein cows using a three-dimensional camera system. *Computers and Electronics in Agriculture*, 111: 186–193.

Knauer, M., Stalder, K.J., Karriker, L., Baas, T.J., Johnson, C., Serenius, T., ... & McKean, J.D. (2007). A descriptive survey of lesions from cull sows harvested at two Midwestern US facilities. *Preventive Veterinary Medicine*, 82(3-4): 198–212.

Knauer, M., Stalder, K., Baas, T., Johnson, C. & Karriker, L. (2012). Physical conditions of cull sows associated with on-farm production records. *Open Journal of Veterinary Medicine*, 2(3): 137.

Knauer, M.T., & Baitinger, D.J. (2015). The sow body condition caliper. *Applied Engineering in Agriculture*, 31(2): 175–178.

Maes, D.G.D., Janssens, G.P.J., Delputte, P., Lammertyn, A., & de Kruif, A. (2004). Back fat measurements in sows from three commercial pig herds: relationship with reproductive efficiency and correlation with visual body condition scores. *Livestock Production Science*, 91(1-2): 57–67.

Patience, J.F.; Thacker, P.A. (1989). *Swine nutrition guide*. Canada: Prairie Swine Center, 260 p.

Salak-Johnson, J.L., Niekamp, S.R., Rodriguez-Zas, S.L., Ellis, M., & Curtis, S.E. (2007). Space allowance for dry, pregnant sows in pens: Body condition, skin lesions, and performance. *Journal of Animal Science*, 85(7): 1758–1769.

Welfare quality®. (2009). *Welfare quality® assessment protocol for pigs (sows and piglets, growing and finishing pigs)*. Lelystad, Netherlands: Welfare Quality® Consortium, 123 p.

Monitoring pig behaviour by RFID registrations

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Abstract

Automation of the monitoring of pig behaviour can support management; deviating behaviour can be an indicator for disease or other disturbances. Registrations of RFID at specific places in a pen can be used to estimate the individual pig behaviour in order to detect abnormalities in drinking and eating behaviour. LF RFID tags were applied to pigs in the period from weaning until the start of the fattening phase. This was done in several experiments at the Dutch Swine Innovation Centre in the South of the Netherlands. In each experiment, 12 pigs were monitored, each equipped with a RFID tag in the right ear. Three readers were installed at the drinking place: (1) and at the feeding trough (2) video recordings were available to validate the results from the processed RFID readings. The performance of the system depended on the established reading distance of the readers. Tag readings were combined into visits by applying a bout criterion. Visits were combined into meals by applying a meal criterion. A good correspondence between tag readings and observed visits was found. A longer reading distance resulted in more tag readings that did not coincide with eating or drinking (but with resting behaviour nearby). Combining the two readers at the feeding trough as if they were one gave better results. The derived visits and meals can be used for detection of deviations on the number per pig per day (or per pig per part of the day). This automated detection can be a valuable tool in pig farming.

Keywords: RFID, pigs, eating behaviour, drinking behaviour

Introduction

Monitoring animal health and welfare is important in pig farming. This task can be supported by the use of data from sensors or other sources. Climate data are a priority to guarantee a quality environment for the pigs. Individual identification with RFID tags can be useful for this monitoring task. The goal of the research project 'Smart Tools for Robust Pigs' is to support these developments. This project is a private-public partnership with KDV (Sustainable Pork Value Chain) and Hotraco as private partners and Wageningen Livestock Research as public research partner. KDV applies individual identification with RFID tags on some farms to guarantee antibiotics-free meat production. The system is based on reading and registration of the RFID numbers of the treated animals in a database, this information is in the slaughterhouse and is used to separate the two different categories (see website sustainable-pork.com for details).

Eating and drinking behaviour can be recorded with RFID tags (Maselyne *et al.*, 2016a, Maselyne *et al.*, 2016b, Maselyne *et al.*, 2018). Tagged animals are recorded when they visit a drinking place or a feeding trough. Several types of RFID systems are available (Ruiz-Garcia and Lunadei, 2011). Mostly HF or UHF RFID systems were used. In this research, an LF RFID system was used to validate the possibilities for monitoring eating and drinking behaviour.

Material and methods

Measurements and observations for this research were done in one pen of the Swine Innovation Centre Sterksel in Sterksel, the Netherlands. This pen was 2.15 m width and 2.64 m long (Figure 1) and equipped with one drinking trough and two combined feeding

troughs. The pen had a slatted floor. During three cycles, 12 pigs were kept in this pen starting at weaning until the start of the fattening phase. This corresponds globally with the phase from four weeks old until nine weeks old. RFID tags were placed on the right ears of the pigs. RFID Reader 1 was installed at the drinker and RFID Reader 2 and 3 at the combined feeders. The reading distance of these readers is flexible: the maximum reading distance was used in Cycle 1 and the minimum reading distance was used in Cycle 3. Feed and water were available ad-lib. In the first two weeks an extra mobile feeding trough was used (without RFID reader). Enrichment materials, like a playing chain, were available for the animals.

Figure 1. Layout of the pen where measurements and observations were done, with an indication of the placement of one drinker and two combined feeders

All RFID readings (RFID number, reader number, date and time) were recorded per second. Multiple readings per reader and second were possible as the system scanned ten times per second. The csv files with readings per day were transferred to an Access database. Video recordings from one camera were available for validation purposes. Stripe patterns were applied on the pigs to make visual identification possible. Each pig was uniquely identified by one to four stripes in blue, green or red. Video recordings were available continuously; six hours during daytime were worked out for recording the eating and drinking behaviour of the individual animals. Weight recordings of the pigs were available at four moments: birth, weaning, start of fattening phase and slaughter. Records were kept of diseases, treatments and other remarks.

Recordings of three cycles were available for the research:

- starting at 27 June 2018;
- starting at 8 August 2018 (without video recordings);
- starting at 19 September 2018.

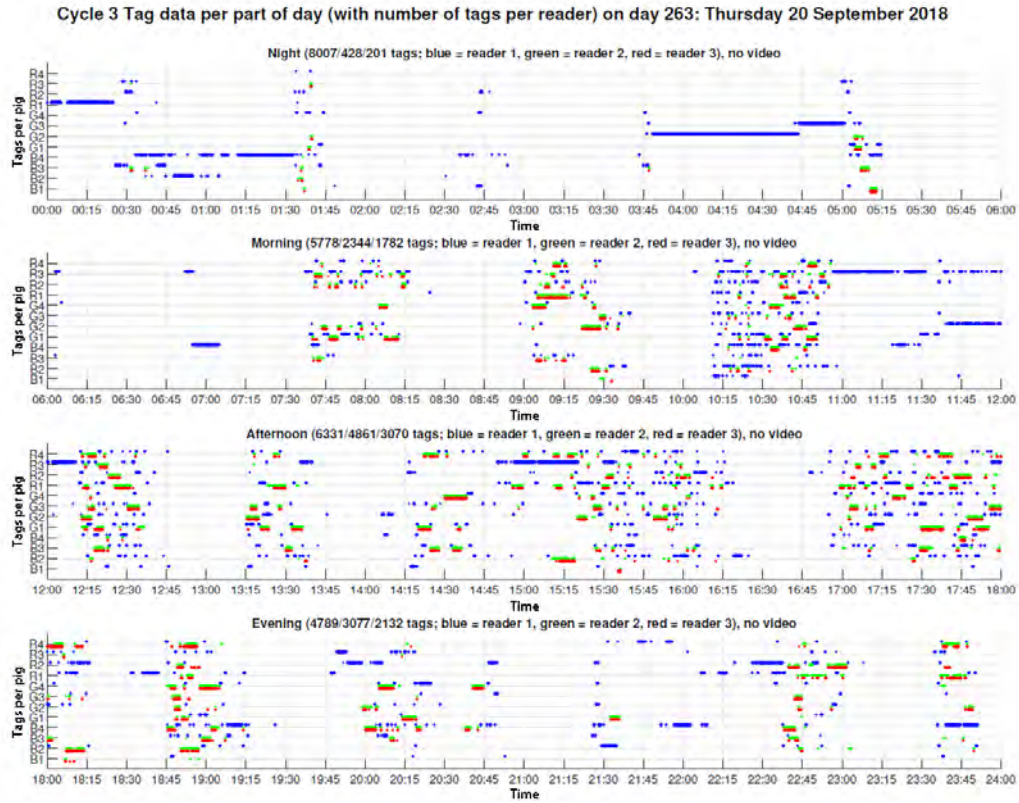

Figure 2. Representation of all tag reading during one day (20 September 2018) during the night (upper figure), the morning (second), the afternoon (third) and the evening (lower); readings from Reader 1 (at the drinking trough) are blue, from Reader 2 are green (left feeding trough) and from Reader 3 are red (right feeding trough)

Recordings of tag readings were available per second for every animal and every reader. An example of the readings of one day is given in Figure 2. Each dot is a reading. Successive readings of the same animal and the same reader result in lines. The readings give the impression that the activity of the animals is fluctuating; intervals without any reading are alternated with intervals where readings from all animals are recorded.

Tag readings were combined into visits. The bout criterion of Maselyne *et al.* (2016b) was used: readings were considered to be in the same visit if the interval between successive readings was less than 20 seconds. For Reader 1 (at the drinker) also the criterion for a length of a visit between 3 and 180 seconds was applied, based on the possible lengths of drinking visits according to Maselyne *et al.* (2016a). Visits with shorter length were deleted and visits with longer length were cut off at 180 seconds. In a second step, visits were combined into meals if the interval between successive visits was less than 14 minutes. This meal criterion was determined by applying the method of Tolkamp and Kyriazakis (1999).

In order to validate the tag readings, video recordings have been analysed by two students, each student analysed three times per hour. Whenever an animal started with eating or drinking, they recorded the time, the animal identification (number and colour of stripes)

and the behaviour: A for Actively for the start of eating/drinking, P for Passively for the end of eating/drinking and L for leaving the eating of drinking trough. For the validation, these recordings were transformed into observed actions, defined as any period starting with a recorded A and ending with a recorded P or L, for any animal or reader.

Results and discussion

The number of tag readings, visits and meals has been determined for Cycle 1 and Cycle 3. The average numbers per day are included in Table 1. The smaller reading distance of the readers applied in Cycle 3 resulted in smaller number of tag readings, but this effect decreased when the tag readings were converted to visits and meals.

Table 1. Average (and standard deviation) of number per day of tag readings, visits and meals per reader and cycle

	Cycle 1 (n = 33)[1]			*Cycle 3 (n = 36)*		
	Tag readings	**Visits**	**Meals**	**Tag readings**	**Visits**	**Meals**
Reader 1	48,968 (8,208)	1,151 (203)	289 (25)	29,242 (7,265)	831 (173)	238 (18)
Reader 2	22310 (4,345)	789 (136)	223 (18)	26,728 (7,888)	808 (155)	206 (16)
Reader 3	10,137 (2,418)	871 (148)	215 (17)	18,134 (5,394)	907 (165)	203 (15)

[1] Two days excluded due to incomplete data collection

The number of tag readings, visits and meals were also available per animal (data not shown). There were clear differences between animals. There were no recorded cases of diseases or other disturbances that might explain these differences.

The average number of tag readings, visits and meals has also been calculated per hour within a day. To illustrate this, the average number of visits per hour are shown in Figure 3 for Cycle 1 and Cycle 3. For Cycle 1, a diurnal pattern was visible with increased activity in the morning and late afternoon. This pattern appeared to be different in Cycle 3 when there was only an increase in the afternoon. No explanation is known for this difference.

For the validation of the tag readings, the observed actions were compared with the tag readings and derived visits per animal and reader. From a preliminary analysis, it appeared worthwhile to combine Reader 2 and 3 into one reader as their distance was small and it was apparently difficult to distinguish these two locations in the observed actions. Therefore, these readers are combined in the further analysis. The length criterions for drinking visits were not applied in the validation phase. An example of the resulting comparison is given in Figure 4.

It can be seen from the comparison in the upper part of Figure 4 that most observed drinking behaviours did correspond with tag recordings and visits. However, the visits could last longer and not each visit corresponded with an observed behaviour. In general, a good correspondence between observed eating behaviours and eating visits can be seen in the lower part of Figure 4. An observed eating behaviour always matched an eating visit (based on tag recordings), and the other way round was also true in most cases.

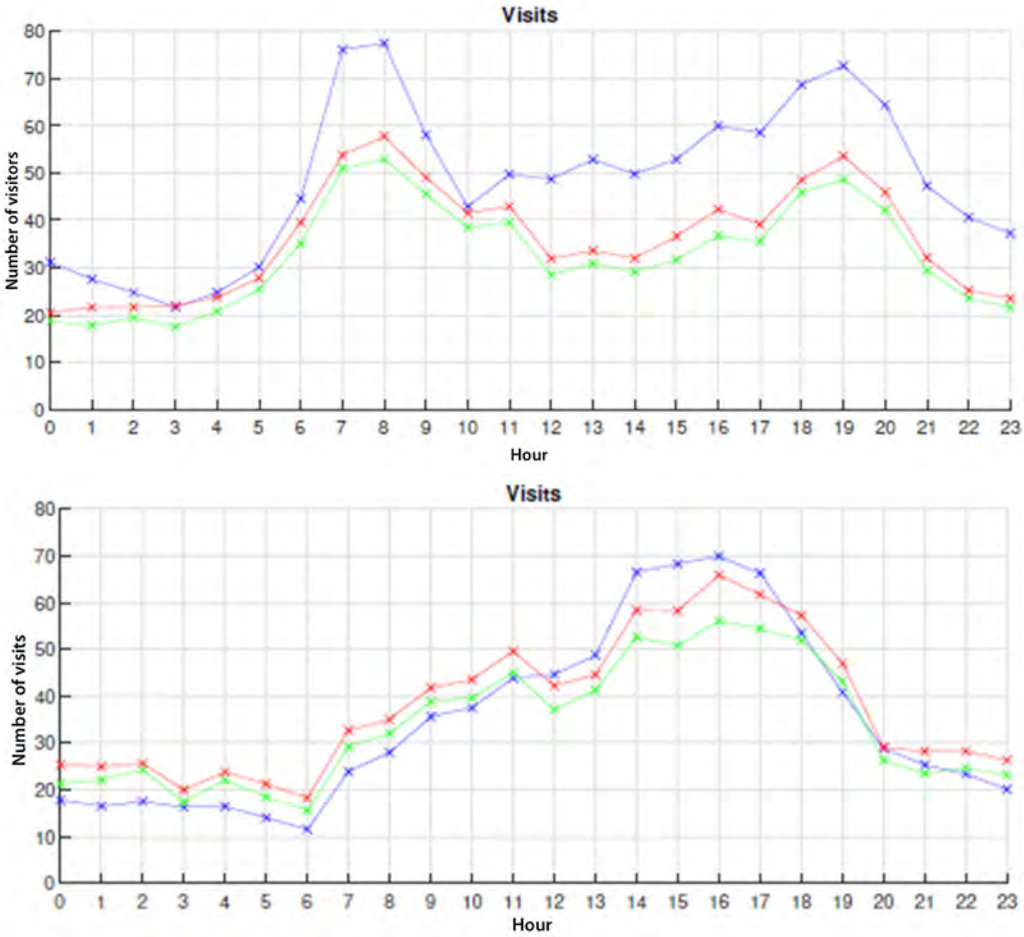

Figure 3. Average of number per hour within day of visits per reader (blue = Reader 1, red = Reader 2, green = Reader 3) for Cycle 1 (upper) and Cycle 3 (lower)

There appeared to be a minor time lag between the tag recordings and the observed behaviours. The time lag used in the analysis varied from 10 - 16 seconds for Cycle 1 and varied from 33–42 seconds for Cycle 3. This time lag was probably due to incorrect synchronization of the time recordings.

The correspondence illustrated in Figure 4 is quantified in Table 2 where the results of the comparison are given for each of the analysed hours. For reader 1, 81% (217 out of 267) of the observed actions did correspond with one or more visits. For Reader 2, this percentage was 97% (176 out of 181). These results implied that most observed actions could also be derived from the tag recording, especially in case of a feeding visit.

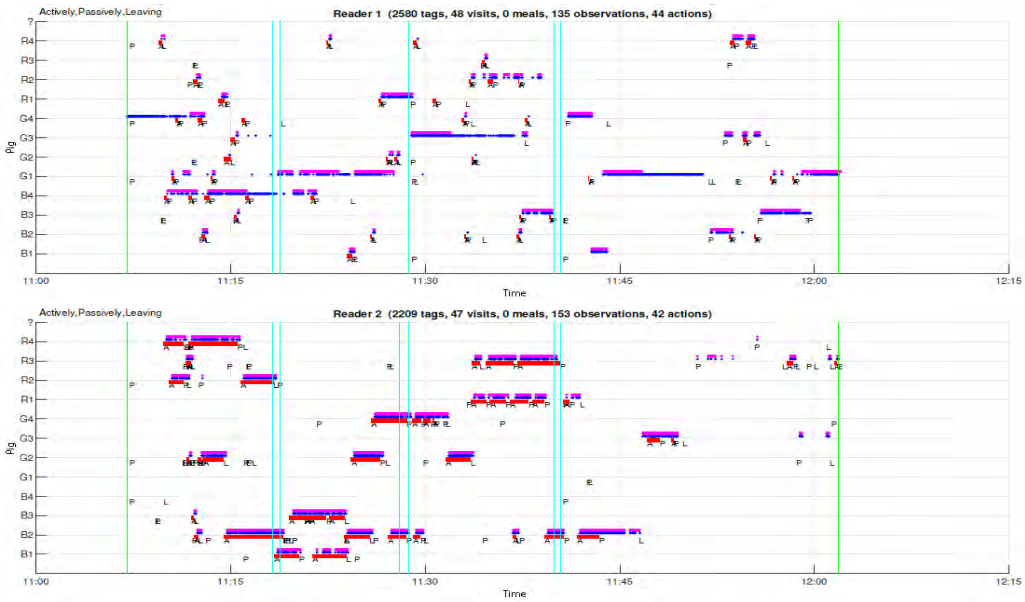

Figure 4. Graphical comparison of tag readings (dark blue) and visits (magenta blocks) with observed actions (red blocks based on observed actions: Actively, Passively and Leaving) for Reader 1 (upper) and Reader 2 (in fact combination of Reader 2 and 3, lower) for the second analysed hour in Cycle 1; green lines delimit the analysis period and light blue lines define human interventions (e.g. noise) in the pen

Table 2. Number of visits and number of visits matching with one or more observed actions, number of observed actions and number of observed actions matching with one or more visits; per reader and analysis period

			Visits	Matching visits	Observed actions	Matching observed actions
Reader 1	Cycle 1	Analysis 1	99	52	59	56
		Analysis 2	65	35	44	38
		Analysis 3	94	20	53	22
	Cycle 3	Analysis 1	96	58	68	65
		Analysis 2	25	19	20	19
		Analysis 3	43	16	23	17
		Total reader 1	422	200	267	217
Reader 2 & 3	Cycle 1	Analysis 1	50	41	45	44
		Analysis 2	47	37	42	42
		Analysis 3	25	14	13	13
	Cycle 3	Analysis 1	68	35	41	39
		Analysis 2	38	8	10	8
		Analysis 3	31	22	30	30
		Total reader 2	259	157	181	176

On the other hand, for Reader 1, 47% of the recorded visits did correspond with one or more observed actions (200 out of 422). For Reader 2, this percentage was 61% (157 out of 259). This implied that not all recorded visits did correspond with observed actions.

These results varied considerably between different analyses; these differences might be due to the circumstances. For example, in Analysis 3 of Cycle 1, only 42% of the observed actions at Reader 1 corresponded with a visit. This might be caused by the fact that the outside temperature was extremely high in a Dutch climate that day (maximum 36.7 ˚C).

These results are very promising; it appears to be possible to monitor drinking and eating behaviour of pigs by analysing readings of LF RFID tags. This method is easy to implement with relatively low costs. Firstly, because a single RFID tag can replace the two required visual Identification and Registration tags (one applied on the farm of birth and second one applied on the farm from where the animal is sent for slaughter). So a part of the labour costs for applying tags can be saved. Secondly, because in this case the RFID tags are also used to separate pigs with and without antibiotics treatment, the recorded behaviour can be applied to detect deviations in the drinking and eating behaviour. Multivariate processing can be used to include individual vs group behaviour, the climate in pen and added data like weight measurements. Automated detection can help the pig farmer in his daily management.

Conclusions

Passive LF RFID tags can be used to monitor eating and drinking behaviour of pigs. 81% of the observed visits to a drinking trough did correspond with recorded visits based on tag readings. This percentage was 97% for visits to an eating trough. Not all recorded visits did correspond with observed visits, filtering might be applied to select real visits. The variation in the results might be explained by differences in climate conditions.

These results imply that RFID readings can be used to measure animal behaviour. So, behaviour can be monitored for detection of diseases and aberrant behaviour.

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References

Maselyne, J., I. Adriaens, T. Huybrechts, B. De Ketelaere, S. Millet, J. Vangeyte, A. Van Nuffel, and W. Saeys. (2016a). Measuring the drinking behaviour of individual pigs housed in group using radio frequency identification (RFID). *Animal,* 10(9): 1557–1566.

Maselyne, J., W. Saeys, P. Briene, K. Mertens, J. Vangeyte, B. De Ketelaere, E.F. Hessel, B. Sonck, and A. Van Nuffel. (2016b). Methods to construct feeding visits from RFID registrations of growing-finishing pigs at the feed trough. *Computers and Electronics in Agriculture,* 128: 9–19.

Maselyne, J., A. Van Nuffel, P. Briene, J. Vangeyte, B. De Ketelaere, S. Millet, J. Van den Hof, D. Maes, and W. Saeys. (2018). Online warning systems for individual fattening pigs based on their feeding pattern. *Biosystems Engineering,* 173: 143–156.

Ruiz-Garcia, L. and L. Lunadei. (2011). The role of RFID in agriculture: Applications, limitations and challenges. *Computers and Electronics in Agriculture,* 79(1): 42–50.

Tolkamp, B.J. and I. Kyriazakis. (1999). To split behaviour into bouts, log-transform the intervals. *Animal Behaviour,* 57(4): 807–817.

Monitoring of approaching farrowing in pens with possibility of temporary crating on the basis of ear tag acceleration data

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Abstract

In most modern pig production systems sows are confined in farrowing crates in a period from entering the farrowing compartment until weaning. This has a negative impact on welfare and health status of sows. One way to reduce this negative impact is to confine sows in crates only in a critical period for piglet survival; from the beginning of farrowing until a few days after farrowing. In order to address this challenge in this study, ear tag based acceleration data were modelled to provide two types of alarms. The experiment took place in the research farm of The University of Veterinary Medicine in Vienna, Austria. The sow herd counted 140 Large White sows in total with 53 animals included in the experiment. Each sow had an ear tag with an accelerometer sensor mounted on the ear. Acceleration data was modelled with Kalman Filtering and Fixed Interval Smoothing (KALMSMO) algorithm. It was possible to predict farrowing on the basis of increased activity in the validation dataset with 1st quartile of 5 h 22 min, median of 8 h 51 min and 3rd quartile of 14 h 1 min before start of farrowing. Alarms indicating the need to confine a sow in a crate were raised with 1st quartile of 1 h 24 min after start of farrowing, median of 2 h 3 min and 3rd quartile of 5 h 38 min before start of farrowing. These results indicate that the developed model should be sufficient to provide early warning for approaching farrowing and secondary alarm indicating the need to confine a sow in a crate.

Keywords: parturition prediction; parturition detection; temporary crating; accelerometer

Introduction

It is a common practice in modern intensive pig husbandry to confine sows in crates, usually for 4-5 weeks, including at least the last few days before the onset of farrowing. The main reason for this practice is to improve piglet welfare by protecting new-born piglets from fatal or injurious crushing by the mother sow (King *et al.*, 2019). These conditions prevent much of the nest-building behaviour (Hansen *et al.*, 2017), an important part of behavioural repertoire in sows, which starts 24 h before parturition, is the most intense 6 - 12 h before parturition and then decreases as parturition approaches (Castrén *et al.*, 1993; Wischner *et al.*, 2009). Increased physiological stress for the sow is a consequence of confinement in a crate (Jarvis *et al.*, 2006).

A concept of temporary crating has been developed as a response to concern about welfare of sows (Moustsen *et al.*, 2012). According to this concept, sows should be temporarily confined in crates only in critical period of piglet lives, when piglet crushing is most probable, in the first 48–72 h after farrowing (Heidinger, B. *et al.*, 2017; Marchant *et al.*, 2000). When the crate is opened the pen offers additional space for the sow, providing a compromise between the needs of the farmer, the sow and her piglets (King *et al.*, 2019). This would allow the sow to stay not confined in crates, in a period of nest-building, at least 24 h before farrowing, which would have positive impact on sows' welfare (Algers, 1994). However, choosing the right moment to confine an individual sow in a crate in farm conditions in a way that makes nest-building possible without increasing the risk of piglet crushing, is challenging.

Automated detection of increase in sow activity related to nest-building behaviour, with use of sensor technology provides a possibility to predict onset of farrowing. This might be useful in practical conditions for farm staff to shorten surveillance intervals by stockmen, and the pen could be prepared for an optimal start of the birthing process (for example, activating a heating source) (Traulsen *et al.*, 2018). However, for the purpose of selecting the optimal time of sow confinement in a crate, in a pen with possibility of temporary crating, so that a sow could stay out of a crate in time of nest-building, there is a need for a reliable method to provide a "second level" alarm additionally to "first level" which indicates when she starts nest-building behaviour. We hypothesise that providing a "second level" alarm at the end of nest-building behaviour should allow confining a sow by farm staff in a crate after nest-building is finished but before farrowing starts. Then, the potential of farrowing pens with possibility of temporary crating to achieve a compromise between the needs of the farmer, the sow and her piglets could be realised.

Thus, the objective of this paper is to model dynamics of ear tag acceleration data in a period before the onset of farrowing to provide "first and second level alarms". Developed techniques should be especially relevant for improving sow welfare in pens with possibility of temporary crating.

Materials and methods

Animals and housing

Experiments were conducted between June 2014 and May 2016 at the experimental farm of the University of Veterinary Medicine Vienna. In total, 53 Austrian Large White sows were included in the experiments. The sows were kept in three types of farrowing pens with possibility of temporary crating of the animals. Out of 53 sows, 18 were kept in SWAP pens (Sow Welfare and Piglet Protection) (Jyden, Vemb, Denmark), 18 in trapezoid pens (Schauer, Prambachkirchen, Austria) and 17 in wing pens (Stewa, Steinhuber, Austria). None of the animals included in the experiments was confined in a farrowing crate from introduction of the animals to farrowing pens until farrowing was finished.

The sows were introduced to the farrowing pens around five days before expected date of farrowing. The date was derived from usual gestation length of sows (114 days) which might vary from 105–125 days. Therefore, it was uncertain when a sow would farrow. The experimental period was from the introduction of sow to the farrowing room until the end of farrowing.

Video recording

Behaviour of sows was video recorded from introduction to the farrowing pens until weaning with 2D cameras in order to create a data set that could be labelled. Each pen was equipped with one IP camera (GV-BX 1300-KV, Geovision, Taipei, Taiwan) locked in protective housing (HEB32K1, Videotec, Schio, Italy) hanging 3 m above the pen, giving an overhead view. Additionally, infrared spotlights (IR-LED294S-90, Microlight, Bad Nauheim, Germany) were installed in order to allow night recording. The images were recorded with 1,280 × 720 pixel resolution, in MPEG-4 format, at 30 fps. The cameras were connected to a PC on which Multicam Surveillance System (8.5.6.0, Geovision, Taipei, Taiwan) was installed.

Data labelling

Recorded videos were manually labelled in order to create a reference data set on the basis of which further data analysis could be performed. In the first step of the labelling process, the time of the beginning of farrowing of each individual sow (n = 53) was labelled. The start of farrowing was defined as the point in time when the body of the first piglet born

dropped on the floor. In the second step, the time of birth of each of the piglets born in a litter was labelled. Time of birth of a piglet was defined as the point in time when the body of the piglet dropped on the floor. Finally, the time of birth of last piglet was labelled that indicated the end of farrowing. Labelling software Interact (version 9 and 14, Mangold International GmbH, Arnstorf, Germany) was used to label the images.

SMARTBOW® system

The SMARTBOW® System (Smartbow GmbH, Weibern, Austria), comprised of ear tags, wall points and station, delivered information on acceleration of sensors attached to sows. The SMARTBOW® ear tag was equipped with an accelerometer sensor that measures acceleration in 3 axes (xyz). The specification of the SMARTBOW® system was described in detail in previous work by Oczak *et al.* (Oczak *et al.*, 2016).

Dataset

For the purpose of modelling acceleration data, 27 (50.9%) sows out of the total of 53 sows included in the experiment were chosen as a training set and 26 (49.1%) as a validation set (Table 1). The animals both in the training set and in the validation set were equally distributed between the wing, trapezoid or SWAP pens. Comparison of statistical measures of effectiveness of the algorithm on training and validation sets enables certain conclusions to be drawn on how well the algorithm could work on other independent datasets.

Table 1. Dataset

Pen type	Training	Validation
Trapezoid	9	9
SWAP	9	9
Wing	9	8
Total	**27**	**26**

Input variable

One variable was used as an input to estimate a model for prediction of farrowing and providing the first and second level alarms. In the first step total physical acceleration (magnitude) was estimated from three axes of accelerometer data (xyz) with an eq.

$$Acc(i) = \sqrt{(x(t)^2 + y(t)^2 + z(t)^2}, \quad t = 1,2,\ldots, N$$

In the above equation Acc(t) is total physical acceleration at a given time point . Three axes of accelerometer data are represented with x(t),y(t) and z(t) at a given time point t.

In the second step total physical acceleration (magnitude) was smoothed with standard deviation calculated on a sliding window of 24 h with 15 min steps. Smoothing window of 24 h allowed elimination of variation in activity of animal related to diurnal rhythm. Steps of 15 min allowed sampling frequent enough for proposed application (Figure 1). The first 12 h of smoothed total physical acceleration was not used as an input to the model. The reason was that activity of a sow in the first hours after introduction to a farrowing pen is increased due to exploration of new environment (Figure 1). These first hours were eliminated to avoid variation in input variable not related to approaching farrowing or nest-building behaviour of sows.

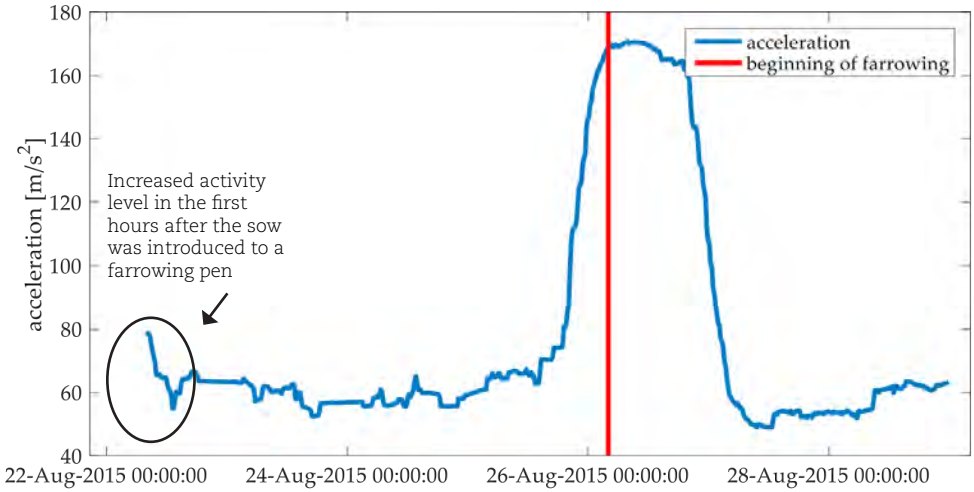

Figure 1. Standard deviation calculated on sliding window of 24 h with 15 min steps. Period depicted in the plot starts from introduction of a sow to a farrowing pen and ends around three days after farrowing

Kalman Filtering and Fixed Interval Smoothing (KALMSMO) algorithm

Input variable (Figure 1) was used to estimate a trend in activity of each sow. Changes in trends (dynamics) in activity of sows were a basis for detection of approaching farrowing and providing first and second level alarms. To estimate the dynamics of activity of sows the Kalman Filtering and Fixed Interval Smoothing (KALMSMO) algorithm was used (Young, 2011) that comprise as special case the Integrated Random Walk.

Data analysis

In the first step, KALMSMO algorithm was applied to an input variable on a fixed interval of 48 h to estimate a level of activity of each sow in a period when the animal is not preparing for farrowing. Nose to variance ratio (Q_nvr) was set on training dataset to 0.000001 to adjust the estimated trend to dynamics of sow's activity.

In the consecutive steps the fixed interval was expended recursively by 15 minutes steps until the trend in animal activity changed to significantly increasing. This was indicated by input variable reaching higher value than upper confidence interval of estimated trend (Figure 2). At this time point the "first level" alarm informing about approaching farrowing was raised.

In the next step KALMSMO algorithm was applied to acceleration data on a fixed interval starting from time point of the "first level" alarm. In the consecutive steps the fixed interval was expended recursively by 15 minutes steps until the trend in animal activity changed to significantly decreasing. This was indicated by input variable reaching lower value than lower confidence interval of estimated trend (Figure 3). At this time point the "second level" was raised. This alarm could be interpreted as an indication to confine a sow in a crate.

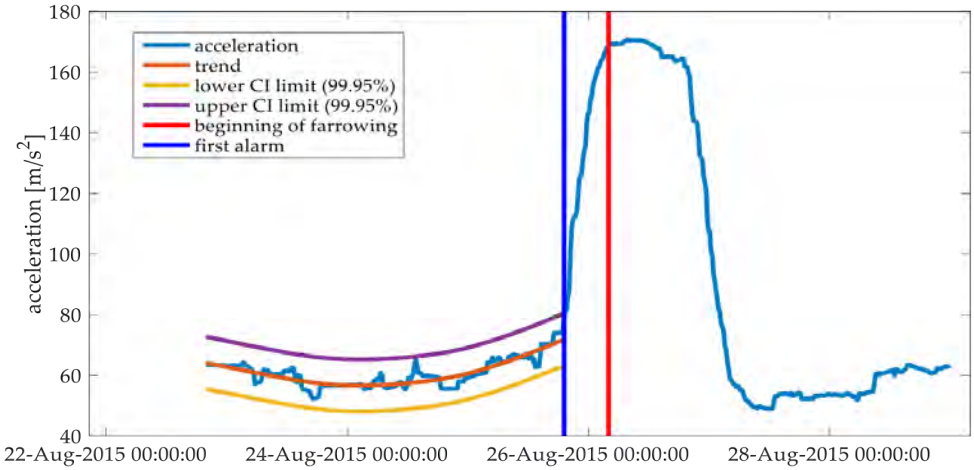

Figure 2. "First level" alarm at 9 h before the onset of farrowing. Period depicted in the plot starts 12 h after introduction of a sow to a farrowing pen and ends around three days after farrowing

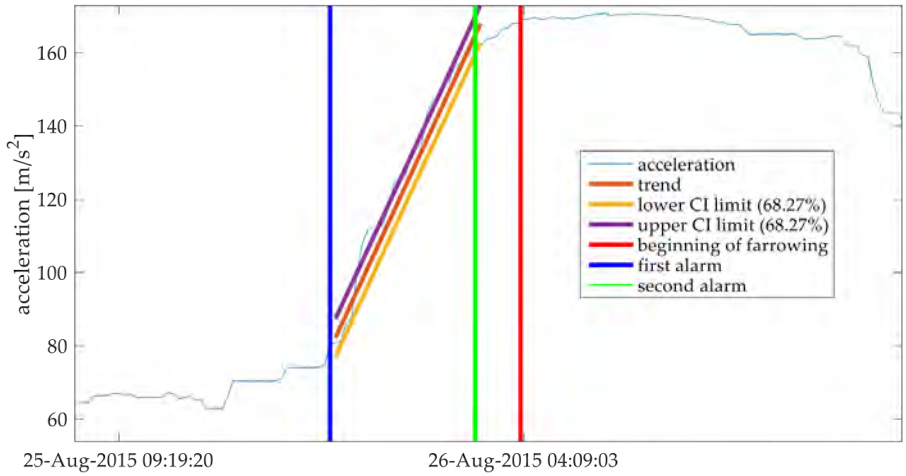

Figure 3. "Second level" alarm at 2 h before the onset of farrowing. Period depicted in the plot starts around 24 h before the onset of farrowing and ends around 24 h after it

Performance of KALMSMO algorithm was evaluated by estimating the duration between time of first "second level" alarms and time of onset of farrowing. Analysis was performed with a commercial software package (MATLAB 2015b, The MathWorks, Inc., Natick, Massachusetts, United States) and function irwsm of CAPTAIN toolbox (Young *et al.*, 2009) was used to fit KALMSMO algorithm.

Results and discussion

Distribution of time of "first and second level" alarms was similar in training and validation datasets. In the training set median of "first level" alarms was 7 h before the onset of farrowing with first quartile of 5 h 6 min and third quartile of 9 h 59 min, while in the validation set median of "first level" alarms was 8 h 51 min with first quartile of 5 h 22 min and third quartile of 14 h 1 min (Figure 4).

These results are similar to results of previous work related to farrowing prediction where individual models were applied to sow activity data (Manteuffel *et al.*, 2015; Pastell *et al.*, 2016; Traulsen *et al.*, 2018). These "first level" alarms can be useful for practical purposes on farms as an alarm within that time window offers the opportunity for targeted attendance to the sow by stockpersons (Traulsen *et al.*, 2018).

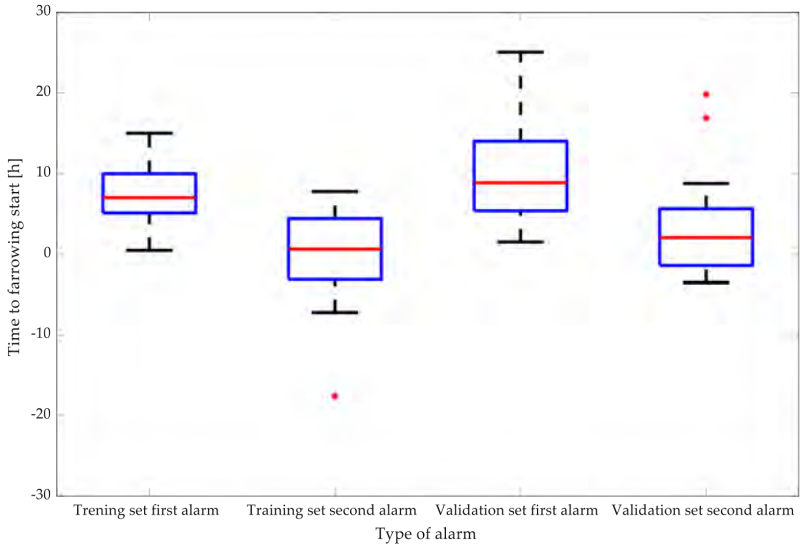

Figure 4. Distribution of alarms in training and validation sets

In the training set median of "second level" alarms was 37 min before the onset of farrowing with 1st quartile of 3 h 8 min after the onset of farrowing and 3rd quartile of 4 h 25 min before the onset of farrowing, while in the validation set the median of second "level alarm" was 2 h 3 min before the onset of farrowing with 1st quartile of 1 h 24 min after the onset of farrowing and 3rd quartile of 5 h 38 min before the onset of farrowing (Figure 4).

In both training and validation datasets, the median of the time of the "second level" alarm was before the onset of farrowing. This might give a possibility to confine a sow in a farrowing crate before the onset of farrowing without too much disturbance for most sows. Still, in many sows the "second level" alarm was raised after the onset of farrowing. This was probably due to the fact that many sows stay active in the beginning of farrowing, with some piglets already born. Thus, activity level itself, measured on the basis of ear tag acceleration data probably can't provide ideal information when farrowing begins.

Although the idea of providing a "second level" alarm was discussed before in scientific literature, for example, in the work of Traulsen *et al.* (2018), to our knowledge this is the first time that a method of this type has been published.

Conclusions

Modelling of changing trends in activity of sows before the onset of farrowing registered with ear tag acceleration data allowed generating "first and second level" alarms. The median time of "first and second level" alarms was before the onset of farrowing in both training and validation sets, with time of "second level" alarms occurring in most sows just before the onset of farrowing (2 h 3 min in validation set). This type of monitoring can

be useful to indicate when a farrowing pen should be prepared for approaching farrowing and when a sow should be confined in a crate in pens with possibility of temporary crating. Potential of farrowing pens with possibility of temporary crating to achieve a compromise between the needs of the farmer, the sow and her piglets might be better realised with application of developed monitoring system.

Acknowledgements

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References

Algers, B. (1994). Health, behaviour and welfare of outdoor pigs. Pig News and Information (United Kingdom).

Anguita, D., Ghio, A., Oneto, L., Parra, X., Reyes-Ortiz, J.L. (2012). Human activity recognition on smartphones using a multiclass hardware-friendly support vector machine, In: Ambient assisted living and home care. Springer, pp. 216–223.

Castrén, H., Algers, B., De Passille, A.-M., Rushen, J., Uvnäs-Moberg, K. (1993). Preparturient variation in progesterone, prolactin, oxytocin and somatostatin in relation to nest building in sows. *Applied Animal Behaviour Science,* 38: 91–102.

Hansen, C.F., Hales, J., Weber, P.M., Edwards, S.A., Moustsen, V.A. (2017). Confinement of sows 24 h before expected farrowing affects the performance of nest building behaviours but not progress of parturition. *Applied Animal Behaviour Science*, 188: 1–8.

Heidinger B, Stinglmayr J, Maschat K, Oberer M, Blumauer E, Kuchling, S., Leeb, C., Hatzmann, E., Zentner, E., Hochfellner, L., Laubichler, C., Dolezal, M., Schwarz. L., Mösenbacher-Molterer, I., Vockenhuber, D., Baumgartner, J. (2017). Evaluation of farrowing systems with the possibility of temporary crating of the sow. Federal Ministry of Agriculture, Forestry, Environment and Water Management of Austria.

Jarvis, S., D'Eath, R.B., Robson, S.K., Lawrence, A.B. (2006). The effect of confinement during lactation on the hypothalamic–pituitary–adrenal axis and behaviour of primiparous sows. *Physiology & Behavior,* 87: 345–352.

King, R., Baxter, E., Matheson, S., Edwards, S. (2019). Temporary crate opening procedure affects immediate post-opening piglet mortality and sow behaviour. Animal: an International Journal of *Animal Bioscience,* 13: 189–197.

Manteuffel, C., Hartung, E., Schmidt, M., Hoffmann, G., Schön, P.C. (2015). Towards qualitative and quantitative prediction and detection of parturition onset in sows using light barriers. *Computers and Electronics in Agriculture,* 116: 201–210.

Marchant, J., Rudd, A., Mendl, M., Broom, D., Meredith, M., Corning, S., Simmins, P. (2000). Timing and causes of piglet mortality in alternative and conventional farrowing systems. *The Veterinary Record*, 147: 214.

Moustsen, V.A., Hales, J., Hansen, C.F. (2012). Farrowing systems with temporary crating. Report of the Free Farrowing Workshop Vienna 2011, pp. 46–48.

Oczak, M., Maschat, K., Berckmans, D., Vranken, E., Baumgartner, J. (2015). Classification of nest-building behaviour in non-crated farrowing sows on the basis of accelerometer data. *Biosystems Engineering,* 140: 48–58.

Oczak, M., Maschat, K., Berckmans, D., Vranken, E., Baumgartner, J. (2016). Can an automated labelling method based on accelerometer data replace a human labeller?–Postural profile of farrowing sows. *Computers and Electronics in Agriculture,* 127, 168–175.

Pastell, M., Hietaoja, J., Yun, J., Tiusanen, J., Valros, A. (2016). Predicting farrowing of sows housed in crates and pens using accelerometers and CUSUM charts. *Computers and Electronics in Agriculture*, 127: 197–203.

Traulsen, I., Scheel, C., Auer, W., Burfeind, O., Krieter, J. (2018). Using Acceleration Data to Automatically Detect the Onset of Farrowing in Sows. Sensors 18, 170.

Wischner, D., Kemper, N., Krieter, J. (2009). Nest-building behaviour in sows and consequences for pig husbandry. *Livestock Science*, 124: 1–8.

Young, P.C. (2011). Recursive estimation and time-series analysis: An introduction for the student and practitioner. Springer Science & Business Media.

Young, P.C., Tych, W., Taylor, C.J. (2009). The CAPTAIN toolbox for matlab. IFAC Proceedings Volumes 42, 758–763.

Use of infra-red thermography to non-invasively assess neonatal piglet temperature

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Abstract

Hypothermia is a significant contributing factor to piglet neonatal mortality. This study assessed the use of an Infra-Red Thermography camera (IRT) to measure piglet temperature in the hour after birth, relative to the gold standard (rectal temperature; RT). At birth (06:00 ± 02:19 min post-partum), 32 piglets were dried, weighed, scored for growth retardation (GR; 0-3), and isolated in a plastic box. Immediately, IRT images were taken at a distance of approx. 1 m from directly above the piglet, followed by RT. The piglet was then returned to the farrowing pen, and the process repeated at approx. 15, 30 and 60 min post-partum. Temperatures of the ear base and tip, and minimum, maximum and average back temperature (shoulders to rump) were extracted with Thermacam Researcher Pro 2.0. Pearson correlations between temperature measures were calculated, and the effect of sex, time, GR score, and weight were included in linear mixed models (SAS 9.4). Temperature at the ear base was most consistently similar to RT across time points ($P > 0.05$), with the ear tip, and minimum back temperature most often different. In general, the worse the GR score, the lower the temperature; ear base and RT were lower in GR 3 piglets than all others ($P < 0.05$). RT was correlated with ear base at more time-points (3) than any other measure. An IR image from the base of the ear taken during the hour after birth could be a reliable, non-invasive method of assessing piglet temperature, and identifying piglets with a lower thermoregulatory ability.

Keywords: Infra-red thermography, rectal temperature, thermoregulation, growth retardation

Introduction

Hypothermia is a cause of neonatal mortality in piglets. Interventions such as drying piglets at birth and placing them near a heat source (heated lamp or mat) helps them to increase their body heat quickly and avoid hypothermia. In addition, providing energy supplement should enhance the thermal status of piglets (Muns *et al.*, 2010). However, providing energy to piglets is rather costly and labour intensive. Thus piglets most in need of supplementation should be identified, as well as the time at which they need it most (e.g. if there is a time when their temperature is likely to drop). One method which can be used to carry out these objectives is to monitor piglets' temperature during the first hour post-partum.

The use of a digital thermometer for measuring rectal temperature has been widely validated and used in research on piglet viability. Recently, infrared thermography imaging has gained interest as a non-invasive technique to measure thermal status of piglets. Soerensen *et al.* (2014) validated the use of the human skin emissivity value of 0.98 for infrared skin measurements on sows. However, the authors highlighted that hairy skin areas or skin with no blood perfusion would have a lower emissivity value. A validation study was conducted by Kammersgaard *et al.* (2013), in which thermal images

and rectal temperatures of piglets were taken at different times between birth and 48 h post-farrowing. Tabuarici *et al.* (2012) found that the temperature of the base of neonatal piglets' ears had a strong positive correlation with their rectal temperature, which suggests this part of the body as being comparable to rectal temperature when assessing thermal status using infra-red thermography.

However, even if thermal imaging has good potential for assessing thermal status of piglets, it may not be able to fully replicate the accuracy of rectal temperature recording to acquire core body temperature. This is due to the potential confounding effects of environmental temperature, huddling of piglets, and presence of birth fluids etc. Indeed, Llamas Moya *et al.* (2006) found that skin temperature was not correlated with birth weight, but was influenced by the huddling behaviour of the piglets and their location relative to a heat source. It is also possible that birth fluids could influence measurements, as the emissivity of wet skin is different from emissivity of dry skin. It is therefore advised that piglets should be dry before taking thermal images and that their behaviour (huddling, feeding, walking) should be observed.

The present study investigated the use of an Infra-Red Thermography camera to measure piglet temperature at several time points during the hour after birth, relative to the rectal temperature (gold standard). In addition, this study aimed to identify characteristics of piglets failing to thermoregulate within 1 h post-partum.

Material and methods

Data collection

This study was conducted in the pig research facilities of Teagasc Moorepark Research Centre, in Fermoy, Co. Cork, Ireland. Piglets were born in conventional farrowing pens (250 × 181 cm) containing a sow crate (225 × 60 cm), a heat pad (155 × 37 cm; 2/3 covered), a water cup and a feeder for piglets. Minimum and maximum room temperatures were monitored daily. Room temperature was maintained at around 23 °C around farrowing and decreased by 0.5 °C/week until weaning.

At birth, 32 piglets (from five litters) were dried and isolated in a plastic box prior to acquiring the first thermal image (at 06:00 ± 02:19 min post-partum), using a FLIR T420 Infra-Red camera. The plastic box represented a controlled environment for the IRT technique, since the temperature and the air flow were the same for all piglets inside this box. Before acquiring pictures, reflected room temperature was measured as the mean temperature of a crunched aluminium foil (emissivity = 1), and air temperature was recorded at the time of each image. These parameters are of high importance for the correct analysis of the thermal images.

Rectal temperature was recorded immediately after the first image was taken, and piglets were then weighed and scored for growth retardation (GR; 0-3). The GR score was attributed based upon on the number of characteristics associated with intra-uterine growth retardation which were displayed by the piglets. These characteristics were classified by Hales *et al.* (2015) as having a dolphin-shape head, bulging eyes and wrinkles around the snout. A score of 0 indicated no GR while a score of 3 indicated severe GR.

Thermal images were acquired at 15, 30 and 60 min post-partum, always followed by the taking of a rectal temperature. Images of the piglets' backs were taken at 1 m distance from the piglet with an angle of 70° (Figure 1a). Thermal images were always taken before rectal temperature in order to minimise handling of the piglets, and potential transmission of the experimenter's heat. In addition, the experimenter wore plastic gloves to further ensure insulation of her hands' heat and minimise handling bias. The time spent handling the

piglets was recorded, especially at birth when the piglets had to be dried. Piglets' behaviour was recorded in between each image acquisition. In particular, the duration of walking, suckling and huddling behaviours were recorded, as well as the time spent on the heat mat.

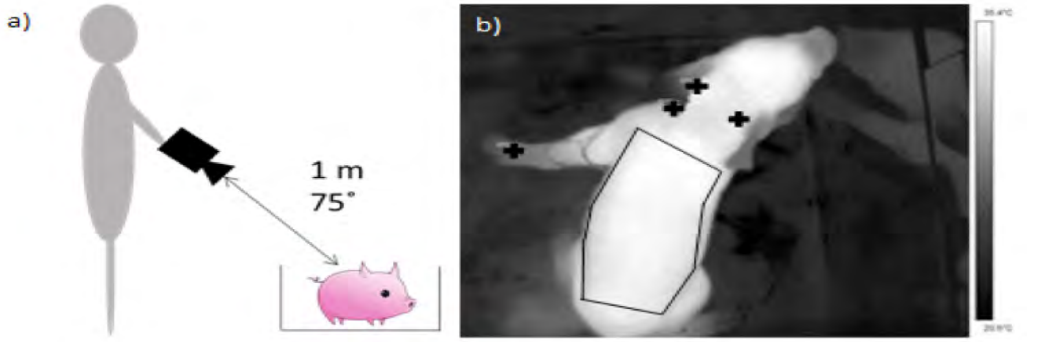

Figure 1. (a) Schematic representation of the positioning of the camera for image acquisition and (b) Example of the infra-red thermography images acquired from piglets

Thermal image analysis

Thermal images were processed with Thermacam Researcher Pro 2.0. Point measurements were placed at the bases and the tips of piglets' ears, and an area was drawn on their back between the shoulders and the rump (see Figure 1b). From this area, the minimum, maximum and average back temperatures were recorded. Temperature data were then entered in an Excel file and analysed normally.

Statistical analysis

Data were analysed using the software SAS 9.4. The statistical unit was the piglet. Pearson correlation tests were performed to investigate the relationship between rectal temperature and temperatures obtained from the thermal images of the piglets' ears (tip and base) and back (minimum, maximum and average). General Linear Models (GLM, PROC MIXED) were used for the investigation of effects of GR score and time post birth on temperature data. The random effect of sow and the repeated effect of time were taken into account in all models. The effect of sex and weight were initially included in all models as covariates, but only sex was kept in the model analysing the minimum temperature of the back.

Results and discussion

Correlations

Table 1 presents the correlations between rectal temperature and the thermal data acquired from the images at different time points. Temperatures of the ear base were positively correlated with rectal temperatures at birth, 30 and 60 min post-partum. Temperatures of the ear tip were positively correlated with rectal temperatures at birth and 30 min post-partum. The maximum and average temperatures of the back area were positively correlated with rectal temperatures at 30 and 60 min post-partum. At 15 min post-partum, none of the data from thermal images were correlated to the rectal temperature.

These results suggest that back and ears are areas of interest for an approximation of the body temperature using infra-red thermography. Nevertheless, when looking at the evolution of thermal status of piglets across time, there seems to be differences between information obtained from the rectal temperature and information obtained from thermal imaging. These differences possibly reflect different mechanisms at play in the thermoregulation process (e.g. heat evaporation and relocation).

Table 1. Pearson correlations coefficients between rectal temperatures and data from thermal images (temperature of the ear tip, ear base, and minimum, maximum and average back temperature) obtained at birth and 15, 30 and 60 min post-partum (pp). *$P < 0.05$, **$P < 0.001$

	Ear tip	Ear base	Min. back	Max. back	Average back
Birth	0.52*	0.47*	0.19	0.29	0.30
15 min pp	0.16	-0.04	-0.14	0.00	-0.04
30 min pp	0.48**	0.88**	0.24	0.82**	0.75**
60 min pp	-0.17	0.61**	0.21	0.59**	0.56**

Factors influencing thermal status

There was an effect of time on all the temperature data, but this effect was different depending on the measurement type. Rectal temperature decreased between birth and 15 min post-partum, remained low until 30 min post-partum, and then increased so that it was similar to that at birth by 60 min post-partum (overall time effect: $F_{3,71.5} = 39.33$, $P < 0.001$; Figure 2). All back temperatures (Table 2) and ear base temperature (overall time effect: $F_{3,72.6} = 34.18$; Figure 3a) increased over time. However, the temperature recorded at the ear tip of piglets decreased between birth and 15 min post-partum, and then increased (overall time effect: $F_{3,75.2} = 7.66$; Figure 3b). These results could indicate that, in the course of thermoregulation process, piglets reallocated heat from the extremities to the vital organs to maintain their (core) body temperature (Whittow *et al.*, 1962).

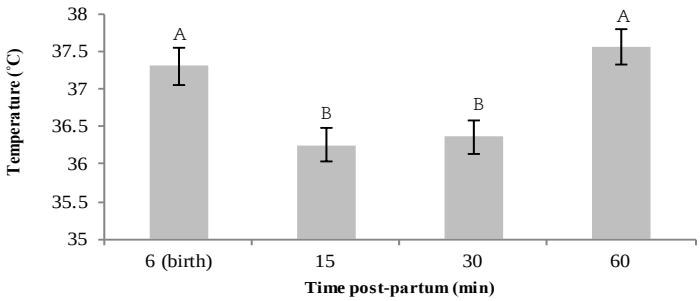

Figure 2. Mean (± S.E.) rectal temperature of neonatal piglets during the first hour after birth. Different letters indicate significant differences (^{A,B} $P < 0.001$)

Table 2. Mean (± S.E.) maximum, minimum and average temperatures of the back area of the piglets, according to the time after birth. Different superscript letters indicate significant differences (^{a,b} $P < 0.05$; ^{A,B} $P < 0.001$)

	Birth (6 min)	15 min post-partum	30 min post-partum	60 min post-partum	F statistics	P-value
Max.	34.3 ^{A} (± 0.36)	34.9 ^{A} (± 0.34)	35.8 ^{B} (± 0.34)	36.9 ^{C} (± 0.34)	$F_{3,69.3}$=35.59	< 0.001
Min.	29.6 (± 0.35)	28.7 ^{A} (± 0.29)	29.2 ^{a} (± 0.28)	30.3 ^{Bb} (± 0.28)	$F_{3,75.4}$=6.31	< 0.001
Avg.	33.1 ^{A} (± 0.40)	33.4 ^{A} (± 0.39)	34.1 ^{B} (± 0.39)	35.2 ^{C} (± 0.39)	$F_{3,73.6}$=37.55	< 0.001

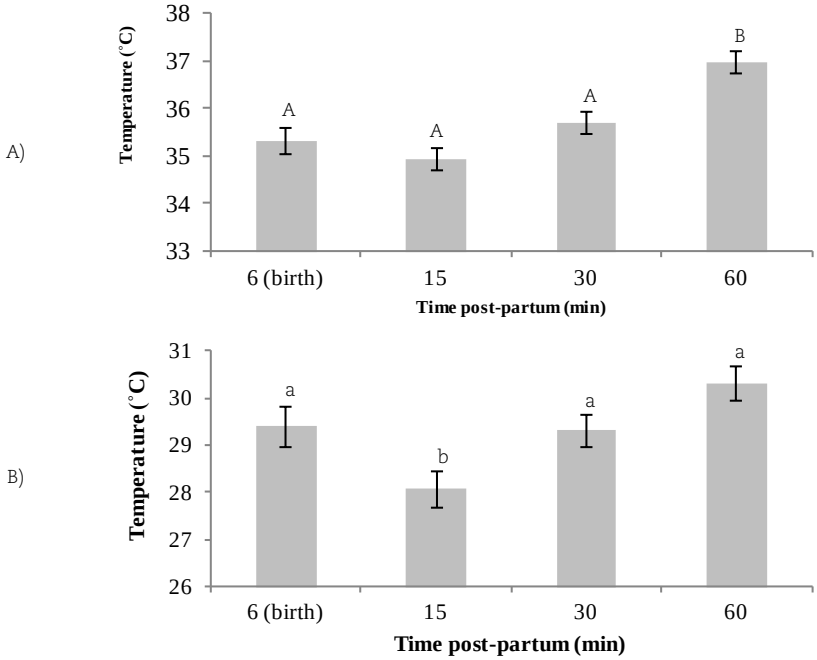

Figure 3. Mean (± S.E.) temperature during the first hour post-partum at the ear base (a) and ear tip (b) of neonatal piglets. Different letters indicate significant differences ([a, b] $P < 0.05$; [A, B] $P < 0.005$)

Overall, the level of growth retardation affected rectal temperature ($F_{3,24.6} = 7.75$, $P < 0.001$; Figure 4a) and temperature of piglets' ear base ($F_{3,24.6} = 4.9$, $P < 0.01$; Figure 4b), and the maximum and average temperature of piglets' back (Table 3). Piglets with the most severe level of growth retardation had lower temperatures than piglets with no growth retardation or an intermediate level of growth retardation. This suggests that piglets with severe growth retardation might have greater difficulty in maintaining good thermoregulation compared with piglets who are not affected by growth retardation. This could be due to their smaller size, with consequently lower energy reserves at birth and a greater surface to body mass ratio which increases heat loss (Herpin *et al.*, 2002).

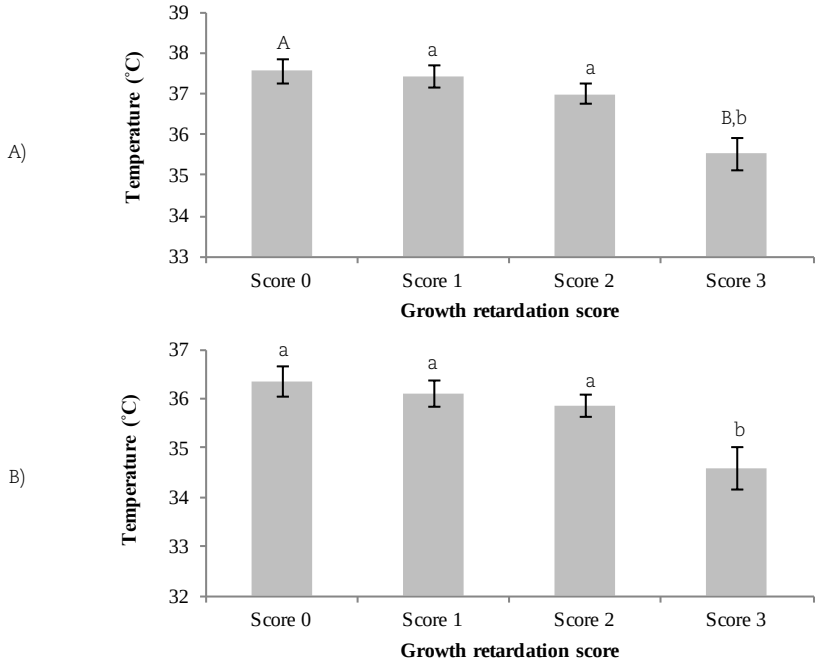

Figure 4. Mean (± S.E.) rectal temperature (a) and temperatures of ear base (b) of piglets according to their growth retardation (GR) score (0 = no GR, to 3 = severe GR). Data presented are the average of all temperatures taken during the first hour post-partum. Different letters indicate significant differences ($P < 0.05$)

Table 3. Mean (± S.E.) maximum, minimum and average temperatures of the back area of the piglets, according to their growth retardation score (score 0 = no growth retardation, score 3 = severe growth retardation). Different superscript letters indicate significant differences ($P < 0.05$)

	Score 0	Score 1	Score 2	Score 3	F statistics	P-value
Max.	35.6 (± 0.40)	35.9 (± 0.36)	36.1 (± 0.34)	34.3 (± 0.52)	$F_{3,23.7} = 4.61$	<0.05
Min.	29.2 (± 0.33)	29.5 (± 0.28)	29.9 (± 0.23)	29.3 (± 0.52)	$F_{3,40.6} = 1.1$	NS
Avg.	34.2 (± 0.44)	34.2 (± 0.41)	34.4 (± 0.40)	33.0 (± 0.53)	$F_{3,25.8} = 3.78$	<0.05

Conclusions

Infra-red images of the base of the ear of neonatal piglets seem to be a valid non-invasive measure of their thermal status. Images taken during the first hour post-partum could be used to determine piglets with difficulties to ensure their thermoregulation. The benefits of using IRT are that the measure is non-invasive, and thus likely to be less stressful for piglets than taking of rectal temperature. This is especially important as it is the piglets which are likely to be more vulnerable (i.e. having difficulty thermoregulating) that the measure is attempting to identify. Use of this measure could prove important in determining which piglets need special attention after birth (e.g. energy supplementation, split suckling, etc.) and thus contribute to reduced mortality and improved welfare for vulnerable piglets. A disadvantage of the method is the cost of the equipment needed to

carry out the measure, but this may break even with improvements in technology, and the potential cost savings associated with reduced mortality. Moreover, besides its use in commercial pig farming, there is ample scope for IRT to be used in a research setting as an alternative to rectal temperature, which not only reduces stress for piglets, but also contributes to promotion of the 3R's (reduction, replacement and refinement) in animal research.

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References

Herpin, P., Damon, M. and Le Dividich, J. (2002). Development of thermoregulation and neonatal survival in pigs. *Livestock Production Science*, 78: 25–45.

Kammersgaard, T.S., Malmkvist, J. and Pedersen, L.J. (2013). Infrared thermography - a non-invasive tool to evaluate thermal status of neonatal pigs based on surface temperature. *Animal*, 7: 2026–2034.

Llamas Moya, S., Boyle, L.A., Lynch, P.B. and Arkins, S. (2006). Influence of teeth resection on the skin temperature and acute phase response in newborn piglets. *Animal Welfare*, 15: 291–297.

Muns, R., Torre, R. de la, Agostini, P.S., Manteca, X. and Gasa, J. (2010). The effect of colostrum supplementation on piglets' body temperature recovery and lactation performance. *Journal of Animal Science*, 88: 306.

Soerensen, D.D., Clausen, S., Mercer, J.B. and Pedersen, L.J. (2014). Determining the emissivity of pig skin for accurate infrared thermography. *Computers and Electronics in Agriculture*, 109: 52–58.

Tabuarici, P., Bunter, K.L. and Graser, H.-U. (2012). Thermal imaging as a potential tool for identifying piglets at risk. In: *AGBU Pig Genetics Workshop*, Armidale, NSW, Australia, pp. 23–30.

Whittow, G. (1962). The significance of the extremities of the ox (Bos taurus) in thermoregulation. *Journal of Agricultural Science*, 58: 109–120.

Animal welfare monitoring by real-time physiological signals

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Abstract

Animal welfare is important and Europe has invested a lot in methods to score or monitor animal welfare in commercial livestock houses. A main objective of Precision Livestock Farming (PLF) is to deliver a tool for active mangement of livestock to improve animal welfare and health and to make livestock farming more animal economically, socially and environmentally sustainable. The importance of well managed animal welfare is not limited to the ethical viewpoint but is also crucial to realise a more efficient process to produce animal products. When considering the metabolic energy balance in a homeothermic living organism, there are different components: basal metabolism, the thermal component, the physical component related to movement or delivering power, the production term (meat, milk, eggs) and finally the mental component. When applying the stress monitoring, developed for humans, on animals we see that we can monitor frustration of horses in real-time. This indicates that real-time animal welfare monitoring based upon physiological signals becomes a realistic pathway.

Introduction

Being a technology driven method PLF takes time for technical people to tune it to the essential part which is the animal. Meanwhile it is a challenge for so called 'animal people' (farmers, veterinarians, animal scientist, nutritionlists, immunologists, etc.) to embrace the potential that this technology has to offer. Animal scientists use many indicators related to a whole range of dissorders from abnormal behaviour, diseases, production failure to poor emotional states (Botreau *et al.*, 2007). Scientists have developed an overall assessment by manual scoring of animal welfare in livestock houses in the field. This method is interesting as a reference method or as a gold standard or for audio-visual labelling of animals in the livestock house. The approach is however not applicable for continuous monitoring of animal welfare since the scoring is done by human observers (Botreau *et al.*, 2009).

Since 2003, when the first ECPLF2003 was organised, the proceedings of the eight bi-annual conferences count over 1,000 publications. Many more per-reviewed papers have been published from which a high number measure components related to animal welfare. With the use of cameras, microphones and sensors, several methods have been developed, tested and validated to monitor components related to animal welfare. For broilers it was shown that animal feature variables like distribution and activity, measured by cameras, are useful to detect over 95% of all noted problems in broiler houses. Gait analysis tools were developed by using cameras and accurate feed intake, monitoring was realised with cameras while vocalisations were analysed for abnormal sounds (Aydin, 2017; Du *et al.*, 2018). For fattening pigs, continuous sound analysis was developed to detect infection and this became a successful commerical product (Berckmans *et al.*, 2015).

For pigs there were many examples of using PLF technology monitoring animal welfare related components such as detection of aggression (Oczak *et al.*, 2014), gait analysis, weight and water intake (Viazzi *et al.*, 2014; Oczak *et al.*, 2014; Kashiha *et al.*, 2013 and 2014; Ismayilova *et al.*, 2013). For cows, PLF systems for body condition scoring, lameness

monitoring, mastitis and ketosis monitoring and feed intake were developed (Van Hertem *et al.*, 2014). We have to confess that most of the technologies so far did not make it yet to large scale applications in livestock houses. So far we have no overall solution to monitor animal welfare in real-time with a scientically based method. The challenge remains to get an overall animal welfare monitor based upon objective measurements.

The objective of this paper was to test whether the real-time monitoring of the metabolic energy balance offers opportunity for continous and real-time monitoring of the mental state of animals while they are active.

Materials and methods

Experimental protocol

The experimental protocol was checked and approved by the ethical commission of the Catholic University of Leuven and the Purdue Animal Care and Use committee (Protocol #111200040). Experiments were done on two individually-housed Large White x Yorkshire pigs, each weighing 20 kg. The pig was placed in a Pig Turn experimental pen (DeBoer *et al.*, 2015) with enough space (1.12 m^2) for an individual animal while wearing a sensor integrated into a harness (Zephyr BioHarness 3). The animal's movement was measured with a 3D accelerometer positioned on the belly of the pig (100 Hz, ±16 G) while heart rate was measured with a belt around the torso just behind the front legs (1 Hz, 25-240 BPM, +- 1 BPM accuracy). Video recordings were taken during the entire experiment to capture animal responses.

During three consecutive days, four experiments were done per day where two types of stressors were applied: a negative stressor and a positive stressor. The negative stressor was a loud sound (120 dB) played for two seconds. The positive stressor was a towel thrown in the test facility as a toy for the pigs to play with (see Table 1).

Table 1. Time schedule of the different stressors

	9 AM	9:30 AM	10 AM	10:30 AM
Day 1	Scare (1)	Towel (1)	Scare (2)	Towel (2)
Day 2	Scare (1)	Towel (1)	Towel (2)	Scare (2)
Day 3	Towel (1)	Scare (1)	Scare (2)	Towel (2)

Method: decomposition of heart-rate in different components

A gold standard for measuring stress, beside questionnaires for humans and audio-visual scoring of animals, is a combined measurement of EEG, ECG, respiration rate, skin conductivity, blood analysis and/or saliva analysis. Several methods have been tested to measure stress based upon physiological data and most of them still need a combination of heart rate with respiration rate or more variables (Hovsepian *et al.*, 2015).

In the past, it was already shown that there is a dynamic relationship between the central nervous system and the expression of emotions and that physiological variables offer potential for monitoring stress (Darwin, 1872; Porges, 1995). The decomposition of heart rate components in mental and physiological or physical components (basal metabolism, movement, power, production, thermal component) remains a challenge on moving subjects, which leads to the consequence that most methods for stress monitoring based on heart rate are limited to non-moving subjects.

We use an algorithm to decompose the total heart rate into three different components:

the baseline, the physical component and the mental component. The assumption in the method is that the animal is acting in the aerobic zone of metabolic energy production. This means that the inhaled air is brought into the blood in the lungs. Then the heart is pumping the blood to the cell level where the metabolic energy is produced. This means that the level of heart rate is a measure for the possible total production of metabolic energy. This metabolic energy is used for the basal metabolism (HR_{BM}), for the thermal component ($HR_{THERM)}$ to keep the body at constant temperature, for the movement energy (HR_{MOV}), for production (HR_{PROD}) and for the mental component (HR_{MENT}). This can be written as:

$$HR_{TOTAL} = HR_{BM} + HR_{THERM} + HR_{MOV} + HR_{PROD} + HR_{MET} \quad (1)$$

Before and during the experiment, the temperature around the animal was kept constant and since this was a short-term experiment we assumed that the production term did not vary enough during the experiment. We can simplify the equation (1) leading to (2):

$$HR_{TOTAL} = HR_{BM} + HR_{MOV} + HR_{MENT} \quad (2)$$

Since every animal is individually different and time varying in the responses to different stressors, the equation must adapt to the individual animal and for this individual be dynamically updated in time.

The measured variables are HR_{TOTAL} and MOVEMENT. The $HR_{BM,}$ normally estimated during night sleep, was estimated here before and during the experiment since that is the non-varying baseline within the signal of total heart rate.

By monitoring in a synchronized way, animal movement using a 3D accelerometer and heart rate, the dynamic responses of total heart rate and movement to stressor can be measured.

To quantify the dynamic response of heart rate to movement during the responses to stressors, a single-input single-output (SISO) linear discrete transfer function model was fitted to the data, using Equation 3:

$$y(k) = \frac{B(z^{-1})}{A(z^{-1})} u(k - \delta) + \xi(k) \quad (3)$$

The terms $A(z^{-1})=1 + a^1 z_{-1} + \cdots + a_n z^{-n}$ and $B(z^{-1}) = b_0 + b_1 z^{-1} + \cdots + b_m z^{-m}$ are the polynomials of the transfer function. In these terms the $a_1,\ldots, a_n$ are the n a-parameters of the nth order A polynomial, and $b_0,\ldots, b_m$ are the m+1 b-parameters of the mth order B polynomial. z^{-1} is the backward shift operator, y is the output (heart rate) and u is the input (movement). k is the time instant of the data point, δ is the time delay, and ξ is the noise of the output error model, which is assumed to be white. By estimating the physical component and basal metabolism of heart rate we finally can also identify the mental component HRMENT showing the mental response to the offered stressors. For a detailed description of this method we refer to the dynamic analyses as used for mental monitoring for humans (Berckmans *et al.*, 2007).

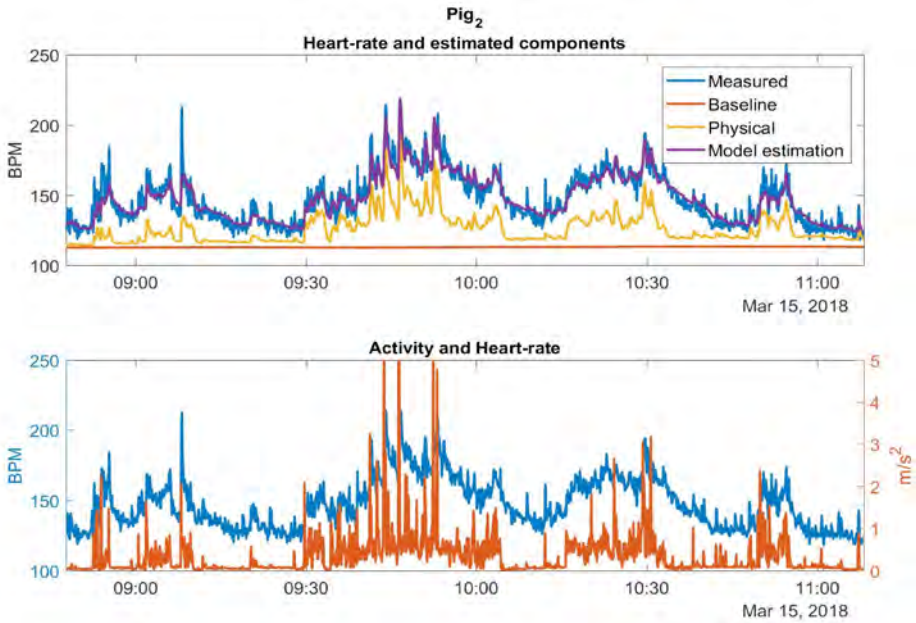

Figure 1. Top: Heart rate and estimated components of Pig 2 on Day 2. Bottom: Raw activity and heart rate as measured by the Zephyr Bio Harness 3

Analysis of the mental component of heart rate to positive and negative stressors

The analysis was focused on the response of the mental component in heart rate to the different stressors. The moment at which each stressor was applied was determined based upon using labelled videos where the stressor was visible. The data were segmented in blocks around each stressor (between two minutes before and two minutes after). Visual qualitative analysis of each response was grouped per pig and per type of stressor (positive or negative).

A statistical analysis was performed for each pig, per type of stressor. The monitored mental heart rate response was grouped together in three groups. The first one contained the data from one minute before application of the stressor until the moment of stress. The second group contained the data from the moment of stress until one minute after. The third group contained the data from one minute after application of the stressor until two minutes after.

It was statistically tested whether groups were significantly different. With the Shapiro Wilks test, the normality of each group was tested (Shapiro *et al.*, 1965). The Friedman test was used to compare three matched groups from a non-Gaussian population (Friedman, 1937). Finally, the Wilcoxon test was used to check whether at least one group was significantly different in a post hoc test (Siegel, 1956).

Results and discussion

Response of mental heart rate component to the negative stressor

The applied negative stressor (loud sound) generated in both pigs a clear increase in the mental component in heart rate after the loud sound was played. Soon after it went back to baseline levels (see Figure 2). The mental component of heart rate can be explained by the animals being scared and this was clearly measurable in real time with sensors on the animal.

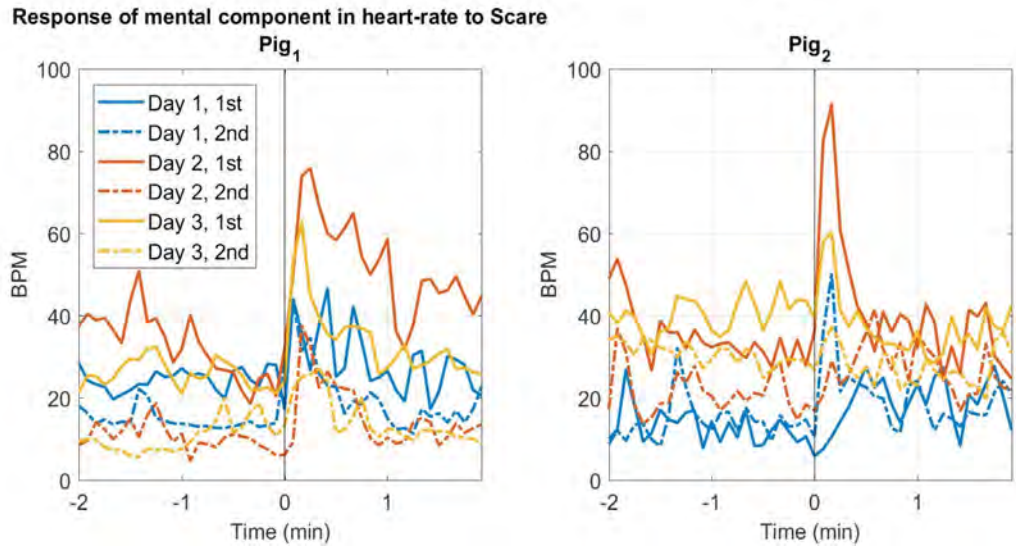

Figure 2. Response of mental component in heart rate of both pigs to the negative stressor (scare with loud sound, applied at time 0)

Response of mental heart rate component to the positive stressor

The applied positive stressor was the access to a towel that generated a playing of the pigs with towel. There was a small increase in the mental component after the towel was thrown in the pen, and the pigs starts playing with it. Most clearly visible for Pig 2 (see Figure 3).

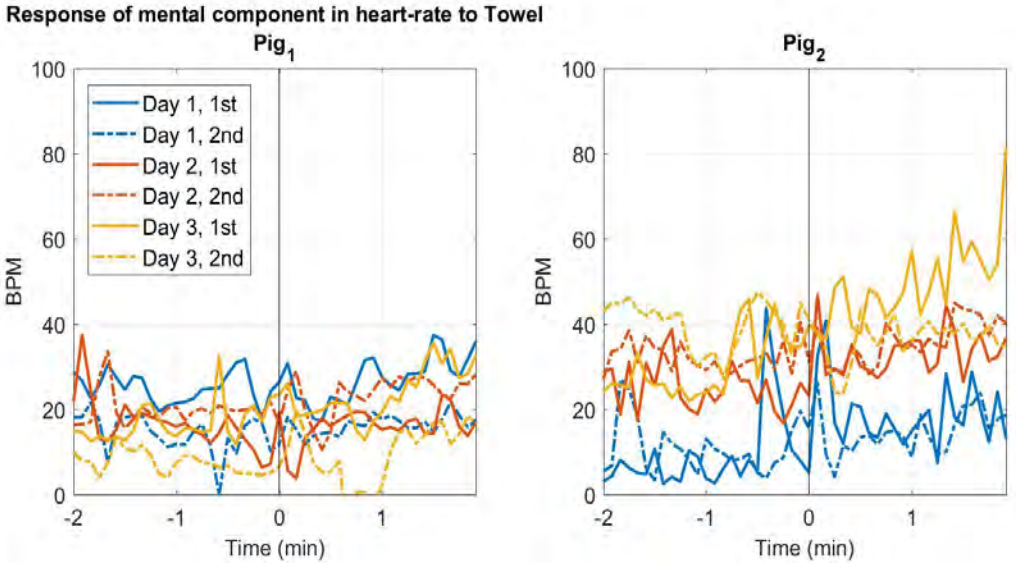

Figure 3. Response of mental component in heart rate of both pigs to the positive stressor (playing with towel thrown in the pen at time 0)

Quantitative statistical analysis of mental responses to negative and positive stressors

The short loud sound as a negative stressor generates a scared response with a corresponding mental heart rate response. The mental component in heart rate increased on average by 13.3 BPM for Pig 1 and by 6.2 BPM for Pig 2 after applying the scare stressor. This increase was found to be significantly different (Figure 4).

After the negative stressor was stopped, the mental component decreased again by on average 9.4 BPM and 4.4 BPM for Pigs 1 and 2, respectively.

The access to a towel as a positive stressor results in the pigs playing with the towel. There was an increase in the mental component when the pigs started playing with the towel that was thrown in their pen. In the two minutes after the towel was given, the mental heart rate increased on average 6.3 BPM and 8.5 BPM for Pigs 1 and 2, respectively, compared to the period one minute before the stressor was applied (see Figure 4 and Table 2).

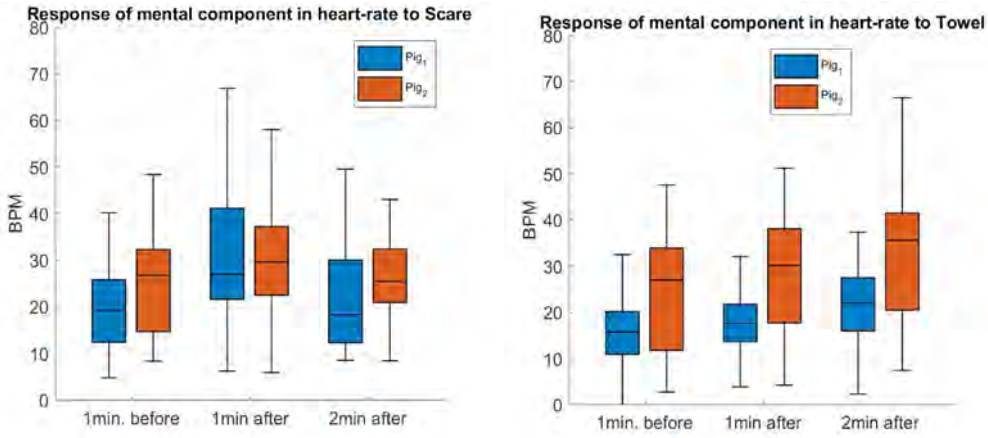

Figure 4. Response of mental component in heart rate to negative (left) and positive (right) stressor

Table 2. Response of mental component in heart rate (Mean ± SD, BPM) to external stressors for two pigs. abc indicate significant differences between the groups ($p < 0.01$, a: 1 minute before, b: 1 minute after and c: two minutes after)

	Scare			Towel		
	1 min. before	**1 min. after**	**2 min. after**	**1 min. before**	**1 min. after**	**2 min. after**
Pig 1	18.8 ± 8.0[bc]	32.1 ± 16.6[ac]	22.7 ± 12.4[ab]	15.7 ±± 6.9[c]	16.8 ± 7.8[c]	22.0 ± 7.2[ab]
Pig 2	24.7 ± 10.9[b]	30.9 ± 15.0[a]	26.5 ± 8.4	25.1 ± 12.8[bc]	29.1 ± 11.9[ac]	33.6 ± 14.6[ab]

Conclusions

It was possible to estimate the mental component in heart rate of pigs while they were moving using wearable sensors on the body of pigs. Two pigs were exposed to a negative and a positive stressor to test whether the method allows to measure mental responses to stressors.

Both pigs respond clearly to the *negative stressor*. In the period of one minute after the stressor was applied, the mental component of heart rate increased significantly ($P < 0.01$)

with on average 13.3 BPM and 6.2 BPM for Pigs 1 and 2 respectively, compared to the period one minute prior. In the period of two minutes after the stressor was applied, the mental component decreased by on average 9.4 BPM ($P < 0.01$) and 4.4 BPM for Pigs 1 and 2, respectively. The mental response to this applied negative loud sound as a stressor was a fast response, only detected immediately after the stressor is applied.

The mental component heart rate of both pigs also responded to the positive stressor, but in a different way. In the period of two minutes after the stressor was applied, the mental component increased significantly ($P < 0.01$) with 6.3 BPM and 8.5 BPM for Pigs 1 and 2, respectively, compared to the period one minute prior to the stressor.

The mental response to the towel as a positive stressor generated a slow response, but this may be affected by the experiment. The towel was not removed, so the pigs were continuously playing with it, as opposed to the negative stressor, which was only applied for a very short period (2 s).

References

Aydin, A. (2017). Development of an early detection system for lameness of broilers using computer vision. *Computers and Electronics in Agriculture,* 136: 140–146.

Berckmans, D., Hemeryck, M., Berckmans, D., Vranken, E., & van Waterschoot, T. (2015). Animal sound…talks! Real-time sound analysis for health monitoring in livestock. *Proc. Animal Environment and Welfare*, 215–222.

Berckmans, D., Quanten, S., Aerts, J.M. (2007). Real-Time Monitoring and Control of Physical and Arousal Status of Individual Organisms. DK2047392, A61B5/024 International GO6F16/00, Application number DK29970784892T, Granted Patent. Pp 120.

Botreau, R., Veissier, I., Butterworth, A., Bracke, M.B.M., Keeling, L.J. (2007). Definition of criteria for overall assessment of animal welfare. *Animal Welfare,* 16(2): 225–228.

Botreau, R.,Veissier, I., Perny, P. (2009). Overall assessment of animal welfare: strategy adopted in Welfare Quality (R). *Animal Welfare,* 18(4): 363–370.

Darwin, C. (1872). The expression of the emotions in man and animals. London, John Murray; Reprinted Chicago, IL, University of Chicago Press, 1965.

DeBoer, S.P., Garner, J.P., McCain, R.R., Lay Jr., D.C., Eicher, S.D. and Marchant-Forde, J.N. (2015). An initial investigation into the effects of social isolation and enrichment on the welfare of laboratory pigs housed in the Pig Turn System assessed using tear staining, behaviour, physiology and haematology. *Animal Welfare*, 24: 15–27.

Fernandez, A.P.,Norton, T.,Tullo, E.,Van Hertem, T., Youssef, A.,Exadaktylos, V.,Vranken, E., Guarino, M., Berckmans, D. (2018). Real-time monitoring of broiler flock's welfare status using camera-based technology. *Biosytems Engineering*, 173: 103–114.

Ferrari, S., Silva, M.,Exadaktylos, V., Berckmans, D., Guarino, M. (2013). The sound makes the difference: the utility of real time sound analysis for health monitoring in pigs. Livestock Housing: Modern management to ensure optimal health and welfare of farm animals. Edited by: Aland, A; Banhazi, T., Pages: 407–417.

Friedman, M. (1937). The use of ranks to avoid the assumption of normality implicit in the analysis of variance. *Journal of the American Statistical Association*, 32(200): 675–701.

Hovsepian, K., al Ábsi, M., Ertin, E., Kamarck, T., Nakajima, M. and Kumar, S. (2015). Towards a gold standard for continuous stress assessment in the mobile environment. Proc ACM Int Conf Ubiquitous Comput, 493–504.

Ismayilova, G., Sonoda, L., Fels, M., Rizzi, R., Oczak, M., Viazzi, S., Vranken, E., Hartung, J., Berckmans, D., Guarino, M. (2013). Acoustic-reward learning as a method to reduce the incidence of aggressive and abnormal behaviours among newly mixed piglets. *Animal Production Science*, art.nr. AN13202.

Kashiha, M., Pluk, A., Bahr, C., Vranken, E., Berckmans, D. (2013). Development of an Early Warning System For a Broiler House Using Computer Vision. Biosystems Engineering, 116(1): 36–45.

Kashiha, M., Bahr, C., Ott, S., Moons, C., Niewold, T., Ödberg, F., Berckmans, D. (2014). Automatic Weight Estimation of Individual Pigs Using Image Analysis. *Computers and Electronics in Agriculture*, 107: 38–44.

Oczak, M., Viazzi, S., Ismayilova, G., Sonoda, L., Roulston, N., Fels, M., Bahr, C., Hartung, J., Guarino, M., Berckmans, D., Vranken, E. (2014). Classification of aggressive behaviour in pigs by activity index and multilayer feed forward neural network. *Biosytems Engineering*, 119: 89–97.

Porges, S.W. (1995). Cardiac vagal tone: a physiological indexx of stress. *Neuroscience and BioBehavioral Reviews,* 19(2): 225–233. Elsevier Ltd, USA.

Shapiro, S.S.; Wilk, M.B. (1965). "An analysis of variance test for normality (complete samples)". *Biometrika*, 52(3–4): 591–611.

Siegel, S. (1956). Non-parametric statistics for the behavioral sciences. New York: McGraw-Hill. pp. 75–83.

Van Hertem, T., Viazzi, S., Steensels, M., Maltz, E., Antler, A., Alchanatis, V., Schlageter Tello, A., Lokhorst, K., Bites Romanini, C., Bahr, C., Berckmans, D., Halachmi, I. (2014). Automatic lameness detection based on consecutive 3D-video recordings. *Biosystems Engineering*, 119: 108–116.

Van Hertem, T., Norton, T., Berckmans, D. (2018). Predicting broiler gait scores from activity monitoring and flock data. *Biosystems Engineering*, 173: 93–102.

Viazzi, S., Ismayilova, G., Oczak, M., Sonoda, L., Fels, M., Guraino, M., Vranken, E., Hartung, J., Bahr, C., Berckmans, D. (2014). Image feature extraction for classification of aggressive interactions among pigs. *Computers and Electronics in Agriculture*, 104: 57–62.

Du, X.D., Lao, F.D, Teng, G.H. (2018). A Sound Source Localisation Analytical Method for Monitoring the Abnormal Night Vocalisations of Poultry. SENSORS, 18, 9, 2906.

Automatic Cattle Monitoring Systems for Precision Livestock Farming

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Abstract

Developments in Precision Livestock Farming (PLF) offer opportunities for automatic animal monitoring technology to enable farmers to detect and control the health and welfare status of their animals at any given time. This paper aims to form a discussion around the proposal of an automatic cattle monitoring system which uses camera technology to identify important attributes relating to animal health and farm management at a herd level as well as at the level of the individual animal. Such a system will allow the farmer's eyes and ears to be replaced wherever a camera can be placed sufficiently close to monitor individual animals.

The system aims to have the capability to recognise cow features from her visual appearance alone which allows for more independent operation and more flexible installation requirements. The system should operate in real-time and be sensitive to the smallest deviations in appearance. This means the farmer can be promptly alerted to potential health issues enabling quicker remedy. The accurate measurement of individual cow nutritional requirements has huge potential when coupled with precise, labour-saving automatic concentrate feeding systems and parlour systems. It opens the possibility for the relationship between feed nutrients and the attributes measured by the system to be discovered for each individual cow. This results in more efficient use of concentrates exactly in accordance with the cow's needs. The system is an essential element of a PLF approach which aims to improve efficiency, animal welfare and environmental friendliness in farming.

Keywords: real-time recognition, image analysis, computer vision

Introduction

The dairy sector is constantly evolving in response to rapidly increasing demand for high-quality dairy products as well as increasing social pressure for better efficiency and environmental sustainability. These changes have resulted in a demand for technologies that can reduce costs and labour inputs while increasing farm productivity. An important aspect of farm automation that is currently being researched is the area of automated animal monitoring by computer vision. In this paper, we discuss the essential requirements of an automatic cattle monitoring system with the ability to identify each animal as well as important attributes relating to cow health and performance. Accurate visual verification of animal ID in feeding bails and milking parlours will ensure correct integration with existing automation equipment such as on-cow activity monitoring devices, yield monitoring sensors, automatic feeding systems and automatic drafting systems. Long-term monitoring of each animals' attributes can yield key information for animal husbandry, ethological studies and the development of PLF tools.

Precision Livestock Farming (PLF) can be defined as real-time monitoring technologies aimed at managing the smallest manageable production unit's temporal variability, known as 'the per animal approach' (Halachmi and Guarino, 2016). Automatically monitoring cattle by intelligent camera surveillance technology could be one of the most important works in PLF. With intense advancements in computer vision and AI, there has arisen an

array of opportunities for these technologies to transform the agricultural sector. This paper will discuss these advances and how they can improve efficiency particularly in the application of computer vision in PLF.

Artificial Intelligence and Computer Vision in Dairy Farming

Artificial Intelligence is one area which has advanced significantly in recent years and there is an opportunity for this new technology to be applied in a wide array of applications in PLF. Intelligent camera surveillance algorithms can be divided into three parts: object detection and identification algorithms, object tracking algorithms, and behaviour analysis algorithms. The core element of any of these algorithms is a feature extractor. Up to recent times, the identification of pose-invariant features of objects required many hours of fine-tuning by human experts for each application. For many decades, classical computer vision techniques advanced very slowly until they were superseded by deep learning in 2015. The development of Convolutional Neural Networks (CNNs) has had a tremendous influence in the field of Computer Vision (CV) in recent years and is responsible for a big jump in the ability to recognise objects. This burst in progress has been enabled by an increase in computing power, as well as an increase in the amount of data available for training neural networks.

3D Vision

Recent works involving the use of 3D vision in agricultural applications have been reviewed based on the recent economic affordability and technological capabilities on offer from optical 3D sensors (Vázquez-Arellano *et al.*, 2016). Image segmentation of traditional 2D images is problematic in real farm conditions. The use of depth information from a 3D camera makes changing backgrounds and shadows less intrusive and enhances the automatic segmentation of different cows as demonstrated by van Nuffel *et al.* (2015). The sensitivity of the camera to natural light, frame rate and field of view are specifications which are continually being upgraded by advancing technology in the field (O'Mahony *et al.*, 2017).

The precision and applicability of measurements gathered from a 3D camera (cameras being placed approximately 0.5 m from the cow) were assessed by (Salau *et al.*, 2017) where teat lengths and heights of ischial tuberosities, i.e. the pins of the cow's pelvis, were calculated from the 3D coordinates. Measurements taken with cattle standing still showed a standard error range from 0.7 - 1.5 mm for teat length and 2.4 - 4.0 mm for the heights of the ischial tuberosities. The accuracy decreases when the animal is moving to 1.8 - 3.2 mm and 14 - 22.5 mm respectively, for each type of measurement. Therefore, the technology is practical for determining accurate measurements for assessing traits in cattle.

Animal Monitoring Applications

Real-time identification of cattle attributes is challenging, but the increasing availability and sophistication of technology make automated monitoring of animals with computer vision practicable. The following section reviews computer vision-based approaches and algorithms which have been implemented for automated scoring of cattle with respect to animal identification, lameness and Body Condition Score (BCS) classification.

Animal Identification

Automatic animal identification can be made through different methods which can be classified as mechanical, electronic and biometric.

Typical mechanical methods include branding, tattoos, ear notching, and ear tags and do not lend themselves to automation. RFID is the leading form of electronic identification in dairy cattle, in fact, Electronic Identification (EID) which uses RFID is mandatory for breeding sheep in Ireland and for cattle in some EU member states. As well as ear tags, devices such as boluses, neck-mounted tags and leg-mounted tags are also used as RFID

transponders. The latter two devices offer greater signal strength and reliability at the cost of greater size and price. RFID transponders can also possibly fail and become detached from the animal and incur a fixed cost per animal.

Biometric identification methods including iris scanning, retinal images and DNA analysis are intrusive to animals and incur a much higher cost compared to other approaches. Biometric identification methods used for animal identification include iris scanning, retinal images and DNA analysis. Machine Vision has been used in preliminary studies to read ear tags (Velez *et al.*, 2013), identify facial features (Kumar *et al.*, 2015), identify muzzle features (Awad, 2016; Kumar, Singh, *et al.*, 2017), identify 3D shape features (Rind Thomasen *et al.*, 2018) and identify cows from overhead (Andrew *et al.*, 2018), (Bercovich *et al.*, 2013).

As summarised by Andrew *et al.* (2018), algorithmic biometric identification was first proved on muzzle images using traditional feature-description algorithms such as Scale-Invariant Feature Transform (SIFT) or Speeded-Up Robust Features (SURF). These semi-automated solutions were improved by approaches which detect the muzzle within the image and classifying on the detected regions alone to achieve 93.3% identification accuracy. Later Kumar, Pandey *et al.* (2017) implemented deep learning to achieve an accuracy of 98.99%.

However, identification by muzzle pattern requires a high-resolution camera, good lighting and a camera to be placed in close proximity to the cow meaning it is not very practical. By placing the camera further away and performing identification from cattle facial representations based on Local Binary Pattern (LBP) texture features, recognition rates up to 95% have been achieved (Cai and Li, 2013).

Cattle identification has also been performed based on tailhead images, allowing the camera to be moved further still from potential fouling and damage. Bercovich *et al.* (2013) formulate a novel body shape signature from the coat patterns of Holstein Friesian cattle and use Fourier descriptors to achieve an accuracy of 99.7%. In more recent work, Andrew *et al.* (2018) demonstrate that computer vision pipelines utilising deep neural architectures are well-suited to perform automated detection of Holstein Friesian cattle (achieving 86.6 accuracy) as well as individual identification (achieving 98% accuracy) in agriculturally relevant setups, i.e. in indoor cattle housing and in outdoor situations with the use of a drone.

While machine vision methodologies for cattle identification have been demonstrated in the literature, the methods developed to date require a lot of human effort to align the reference cow IDs with the images used to train the system. Another critique is that while identification by overhead cameras is very practical, many of the systems developed have only been proven on Holstein Friesian cattle which are distinctive for exhibiting individually-unique black & white (or brown & white) coat patterns, patches and markings over their bodies. Such a system is unlikely to be effective on cattle breeds without individually-unique coat patterns. Although visual identification systems are advantageous in terms of applicability, cost-effectiveness and precision, most of the image processing algorithms used in these solutions are influenced by external conditions such as variable light conditions, reflections and lens fouling. Changes in animal posture and change in size according to distance are other possible issues. To overcome these challenges, 3D cameras seem to offer a solution and preliminary work done by Arslan *et al.* (2014) proves the applicability of 3D cameras to the problem albeit with a small test set.

Although using biometric identifiers has proved suitable for use in computerised identification systems, it raises additional challenges in terms of identifier capturing, identification accuracy, processing time, and overall system operability (Awad, 2016). For instance, in a purely automatic deployment of a cattle identification system requires for the ground truth cow IDs to be established by some means. One solution is to interface

with an RFID Identification System but who is to say that the IDs retrieved from this system are accurate? If erroneous IDs are collected the system is thrown off, therefore there needs to be some means of manual intervention to automatically identify and alert the farmer to erroneous matches between the vision system and the external reference system.

Lameness Detection

As lame cows produce less milk and tend to have other health problems, finding and treating lame cows is very important for farmers. Lameness persists as a specific welfare concern and although the true level of incidence it is unknown, the typical average value is 50 limb cases per 100 cow-years (Archer *et al.*, 2010).

The active monitoring and prevention of lameness at a herd level often requires the involvement of a vet or some other trained observer. However, lame cows are often undiagnosed until the problem has become severe. Sensors (vision and non-vision) that measure behaviours associated with lameness in cows can help by alerting the farmer of those cows in need of treatment. Automated monitoring solutions avoid animal interference or handling, and observer bias. Moreover, automatic sensing can spot things humans cannot by accumulating observations over extended periods of time, in some situations 24 hours a day, in contrast to human observers who look at animals for a few minutes or even seconds. The state-of-the-art in automatic lameness detection is summarised in Table 1 under categories such as the size of the test dataset, the degree of automatization, the type of camera and the accuracy achieved.

Table 1. Past Vision-based Locomotion Scoring Research

Features	Reference	Number of cows tested	Automated	Accuracy (%)
Trackway overlap, hoof step time and spine arch	(Berckmans *et al.*, 2008)	15	No	
Hoof step time and corresponding time between hoof combinations	(Bahr *et al.*, 2008)	15	No	
Spine curvature and head angle	(Poursaberi *et al.*, 2011)	1,200	No	92
The range of motion of the front hooves and the release angle of the front hooves	(Pluk *et al.*, 2012)		No	
Hook bones and spine	(Abdul Jabbar *et al.*, 2017)		No	
A body movement pattern score individualized to each cow	(Viazzi *et al.*, 2014).		No	91
Curvature angle of back around hip joints and back posture measurement	(van Hertem *et al.*, 2018)		Yes	
Hoof location determined by CNN	(Gardenier *et al.*, 2018)		Yes	

Despite the amount of research, no efficient automated lameness detection system is available on the market yet. Most research on lameness detection focuses on the detection

of severely lame cows, often ignoring mildly lame cows or considering them non-lame. On the other hand, the practical feasibility of also detecting the mildly lame cases should be investigated on farms. This might result in custom-made lameness detection systems that are adjustable depending on the degree and severity of mildly and severely lame cases on that farm and the preferences of the farmer for specific characteristics of the system.

Van de Gucht *et al.* (2017) have simulated the effect of detection performance (percentage missed lame cows and percentage false alarms) and system cost on the potential market share of three automatic lameness detection systems relative to visual detection: a system attached to the cow, a walkover system, and a camera system. Based on survey responses, systems attached to the cow had the largest market potential but were still not competitive with visual detection. Increasing the detection performance or lowering the system cost led to higher market shares for automatic systems at the expense of visual detection. The willingness to pay for extra performance was €2.57 per cow for every 1% fewer missed lame cows, €1.65 per cow for every 1% fewer false alerts, and €12.7 per cow for lame leg indication.

Table 2. Past Vision-based Body Condition Scoring Research

Features	Reference	Size of test dataset (images)	Automated/ 3D/2D	Accuracy (%) or R statistic
Hook angle, posterior hook angle, depression	(Bewley *et al.*, 2008)	834	No/2D	92.79
Wither height, hip height, body length and hip width	(Tasdemir *et al.*, 2011)	-	No/3D	BCS not estimated
Goodness of fit of a parabolic shape of the segmented image	(Halachmi *et al.*, 2008), (Halachmi *et al.*, 2013)	172	Yes/2D	R=0.94
'Pins', base of the tail, dishes of the rump, hips, and backbone	(Weber *et al.*, 2014)	-	No/3D	-
Principal component analysis	(Fischer *et al.*, 2015)	25	No/3D	R=0.96
14 individual features per cow, derived from cows' topography	(Spoliansky *et al.*, 2016)	2,650	Yes/3D	74%
Area around the tailhead and left and right hooks	(Lynn *et al.*, 2017)	130	Yes/2D	-
Body mass, hip height and withers height	(Nir *et al.*, 2017)	107	Yes/3D	R^2 = 0.946 for body mass
3D surface of cows back and fitted sphere	(Hansen *et al.*, 2018)	95	Yes/3D	-
Features determined by CNN on pre-processed depth images	(Rodríguez Alvarez *et al.*, 2018)	503	Yes/3D	78%

Body Condition Scoring

Body Condition Score (BCS) is an indirect estimation of the level of body reserves, and its variation reflects cumulative variation in energy balance. It interacts with reproductive and health performance, which are important to consider in dairy production but not easy to monitor. Manual visual BCS is subjective, time-consuming and requires experienced employees. The state-of-the-art in automatic BCS estimation is summarised in Table 2 under categories such as the size of the test dataset, the degree of automatization, the type of camera used and the accuracy of scores within 0.25 of manual BCS reference.

Discussion

This review of the state-of-the-art research in Cow ID, locomotion score and BCS estimation shows a trend towards more automated approaches which make use of 3D cameras and deep learning for automatic feature extraction, improved accuracy and more reliable operation. Many of the works have focused on Holstein Friesian cattle and a system is yet to be developed which can be universally applied to any breed. Another point of note is that variables such as lactation stage and parity have been shown to have an effect on BCS and locomotion which may need to be accounted for in the development of such a system (Weber *et al.*, 2014; van Hertem *et al.*, 2018).

Conclusions

This paper identifies the essential technologies and considerations for the development of an automatic cattle monitoring system which uses camera technology to identify important attributes relating to cow health and performance. The system should have the capability to recognise cow features from her visual appearance alone which allows for more independent operation and more flexible installation requirements. The system would be limited to indoor environments where the required communications infrastructure between camera and base can be easily installed. However, the system should provide real-time insights to allow decisions to be made at critical points in a pasture-based management system – when the cow is being fed concentrates, when the cow is being milked and when the cow is being drafted. The algorithms should also make use of AI for improved accuracy and reliability in a diverse range of conditions considering that poor lighting and lens fouling are likely to occur in farmyard environments. The potential for the system to extract appearance attributes of cattle is an interesting one and could be invaluable in integrating with feeding systems to manage cow nutrition more effectively and alerting the farmer to ill health promptly.

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References

Abdul Jabbar, K., Hansen, M.F., Smith, M.L. and Smith, L.N. (2017). 'Early and non-intrusive lameness detection in dairy cows using 3-dimensional video', *Biosystems Engineering*, 153.

Andrew, W., Greatwood, C. and Burghardt, T. (2018). 'Visual Localisation and Individual Identification of Holstein Friesian Cattle via Deep Learning'. Institute of Electrical and Electronics Engineers, pp. 2850–2859.

Archer, S., Bell, N. and Huxley, J. (2010). 'Lameness in UK dairy cows: a review of the current status', *In Practice*. British Medical Journal Publishing Group, 32(10), pp. 492–504.

Arslan, A.C., Akar, M. and Alagoz, F. (2014). '3D cow identification in cattle farms', in *2014 22nd Signal Processing and Communications Applications Conference (SIU)*. IEEE, pp. 1347–1350.

Awad, A.I. (2016). 'From classical methods to animal biometrics: A review on cattle identification and tracking', *Computers and Electronics in Agriculture*, 123: 423–435.

Bahr, C., Leroy, T., Song, X., Maertens, W., Vranken, E., Nuffel, A. van, Vangeyte, J., Sonck, B. and Berckmans, D. (2008). 'Automatic detection of lameness in dairy cattle by vision analysis of cow's gait', *Agricultural and biosystems engineering for a sustainable world. International Conference on Agricultural Engineering, Hersonissos, Crete, Greece, 23-25 June, 2008*. European Society of Agricultural Engineers (AgEng).

Berckmans, D., Bahr, C., Leroy, T., Song, X., Vranken, E., Maertens, W., Vangeyte, J., Nuffel, A.V. and Sonck, B. (2008). *Automatic detection of lameness in dairy cattle - Analyzing image parameters related to lameness.*, *Livestock Environment VIII - Proceedings of the 8th International Symposium*. American Society of Agricultural and Biological Engineers-ASABE.

Bercovich, A., Edan, Y., Alchanatis, V., Moallem, U., Parmet, Y., Honig, H., Maltz, E., Antler, A. and Halachmi, I. (2013). 'Development of an automatic cow body condition scoring using body shape signature and Fourier descriptors', *Journal of Dairy Science*. Elsevier, 96(12): 8047–8059.

Bewley, J.M., Peacock, A.M., Lewis, O., Boyce, R.E., Roberts, D.J., Coffey, M.P., Kenyon, S.J. and Schutz, M.M. (2008). 'Potential for Estimation of Body Condition Scores in Dairy Cattle from Digital Images', *Journal of Dairy Science*. Elsevier, 91(9): 3439–3453.

Cai, C. and Li, J. (2013). *Cattle Face Recognition Using Local Binary Pattern Descriptor*.

Fischer, A., Luginbühl, T., Delattre, L., Delouard, J.M. and Faverdin, P. (2015). 'Rear shape in 3 dimensions summarized by principal component analysis is a good predictor of body condition score in Holstein dairy cows', *Journal of Dairy Science*.

Gardenier, J., Underwood, J. and Clark, C. (2018). 'Object Detection for Cattle Gait Tracking', *2018 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 2206–2213.

van De Gucht, T., van Weyenberg, S., van Nuffel, A., Lauwers, L., Vangeyte, J. and Saeys, W. (2017). 'Supporting the Development and Adoption of Automatic Lameness Detection Systems in Dairy Cattle: Effect of System Cost and Performance on Potential Market Shares', *Animals*, 7(12): 77.

Halachmi, I., Polak, P., Roberts, D.J. and Klopcic, M. (2008). 'Cow Body Shape and Automation of Condition Scoring', *Journal of Dairy Science*.

Halachmi, I., Klopčič, M., Polak, P., Roberts, D.J. and Bewley, J.M. (2013). 'Automatic assessment of dairy cattle body condition score using thermal imaging', *Computers and Electronics in Agriculture*. Elsevier, 99: 35–40.

Halachmi, I. and Guarino, M. (2016). 'Editorial: Precision livestock farming: a "per animal" approach using advanced monitoring technologies', *Animal*, 10(09): 1482–1483.

Hansen, M.F., Smith, M.L., Smith, L.N., Abdul Jabbar, K. and Forbes, D. (2018). 'Automated monitoring of dairy cow body condition, mobility and weight using a single 3D video capture device', *Computers in Industry*. Elsevier, 98, pp. 14–22.

van Hertem, T., Schlageter Tello, A., Viazzi, S., Steensels, M., Bahr, C., Romanini, C.E.B., Lokhorst, K., Maltz, E. and Halachmi, I. (2018). 'Implementation of an automatic 3D vision monitor for dairy cow locomotion in a commercial farm', *Biosystems Engineering*. Academic Press, 173: 166–175.

Kumar, S., Pandey, A., Sai Ram Satwik, K., Kumar, S., Kumar Singh, S., Kumar Singh, A., Mohan, A., Kumar, S., Pandey, A., Kumar Singh, S., Kumar Singh, A. and Mohan, A. (2017). 'Deep Learning Framework for Recognition of Cattle using Muzzle Point Image Pattern'.

Kumar, S., Singh, S.K., Singh, R. and Singh, A.K. (2017). 'Muzzle Point Pattern-Based Techniques for Individual Cattle Identification', in *Animal Biometrics*. Singapore: Springer Singapore, pp. 111–135.

Kumar, S., Tiwari, S. and Singh, S.K. (2015). 'Face recognition for cattle', in *2015 Third International Conference on Image Information Processing (ICIIP)*. IEEE, pp. 65–72.

Lynn, N.C., Kyu, Z.M., Zin, T.T. and Kobayashi, I. (2017). 'Estimating body condition score of cows from images with the newly developed approach', in *2017 18th IEEE/ACIS International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD)*. IEEE, pp. 91–94.

Nir, O., Parmet, Y., Werner, D., Adin, G. and Halachmi, I. (2017). '3D Computer-vision system for automatically estimating heifer height and body mass', *Biosystems Engineering*. Academic Press.

van Nuffel, A., Zwertvaegher, I., van Weyenberg, S., Pastell, M., Thorup, V.M., Bahr, C., Sonck, B. and Saeys, W. (2015). 'Lameness detection in dairy cows: Part 2. Use of sensors to automatically register changes in locomotion or behavior', *Animals*.

O'Mahony, N., Murphy, T., Panduru, K., Riordan, D. and Walsh, J. (2017). 'Real-time monitoring of powder blend composition using near infrared spectroscopy', in *2017 Eleventh International Conference on Sensing Technology (ICST)*. IEEE, pp. 1–6.

Pluk, A., Bahr, C., Poursaberi, A., Maertens, W., van Nuffel, A. and Berckmans, D. (2012). 'Automatic measurement of touch and release angles of the fetlock joint for lameness detection in dairy cattle using vision techniques.', *Journal of Dairy Science*. Elsevier, 95(4): 1738–48.

Poursaberi, A., Bahr, C., Pluk, A., Berckmans, D., Veermae, I., Kokin, E. and Pokalainen, V. (2011). 'Online lameness detection in dairy cattle using Body Movement Pattern (BMP)', in *2011 11th International Conference on Intelligent Systems Design and Applications*. IEEE, pp. 732–736.

Rind Thomasen, J., Lassen, J., Gunnar Brink Nielsen, G., Borggard, C., René, P., Stentebjerg, B., Hansen, R.H., Hansen, N.W. and Borchersen, S. (2018). 'Individual cow identification in a commercial herd using 3D camera technology', in *World Congress on Genetics Applied to Livestock Production*, p. 613.

Rodríguez Alvarez, J., Arroqui, M., Mangudo, P., Toloza, J., Jatip, D., Rodríguez, J.M., Teyseyre, A., Sanz, C., Zunino, A., Machado, C. and Mateos, C. (2018). 'Body condition estimation on cows from depth images using Convolutional Neural Networks', *Computers and Electronics in Agriculture*, 155: 12–22.

Salau, J., Haas, J.H., Junge, W. and Thaller, G. (2017). 'A multi-Kinect cow scanning system: Calculating linear traits from manually marked recordings of Holstein-Friesian dairy cows', *Biosystems Engineering*, 157.

Spoliansky, R., Edan, Y., Parmet, Y. and Halachmi, I. (2016). 'Development of automatic body condition scoring using a low-cost 3-dimensional Kinect camera', *Journal of Dairy Science*. Elsevier, 99(9): 7714–7725.

Tasdemir, S., Urkmez, A. and Inal, S. (2011). 'Determination of body measurements on the Holstein cows using digital image analysis and estimation of live weight with regression analysis', *Computers and Electronics in Agriculture*. Elsevier, 76(2): 189–197.

Vázquez-Arellano, M., Griepentrog, H.W., Reiser, D. and Paraforos, D.S. (2016). '3-D imaging systems for agricultural applications—a review', *Sensors (Switzerland)*.

Velez, J.F., Sanchez, A., Sanchez, J. and Esteban, J.L. (2013). 'Beef identification in industrial slaughterhouses using machine vision techniques', *Spanish Journal of Agricultural Research*.

Viazzi, S., Bahr, C., van Hertem, T., Schlageter-Tello, A., Romanini, C.E.B.E.B., Halachmi, I., Lokhorst, C. and Berckmans, D. (2014). 'Comparison of a three-dimensional and two-dimensional camera system for automated measurement of back posture in dairy cows', *Computers and Electronics in Agriculture*. Elsevier, 100, pp. 139–147.

Weber, A., Salau, J., Haas, J.H., Junge, W., Bauer, U., Harms, J., Suhr, O., Schönrock, K., Rothfuß, H., Bieletzki, S. and Thaller, G. (2014). 'Estimation of backfat thickness using extracted traits from an automatic 3D optical system in lactating Holstein-Friesian cows', *Livestock Science*. Elsevier, 165: 129–137.

Predicting the next life event of cows by applying deep learning on sequential and pictorial data

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Abstract

In this research, we investigate whether a cow's future state such as calving, sickness or even death can be predicted based on its history of recorded fertility and disease events. In particular, we show how Markov for discrimination models (**MFD**) can estimate the posterior class probabilities and how deep learning algorithms such as Long Short Term-Memory networks (**LSTM**) can improve the classification accuracy. Additionally, we also investigate whether data augmentation with pictorial information can enhance the predictive performance even further by using convolutional neural networks (**CNN**). Results show that an ensemble model incorporating sequential as well pictorial information performs best and that the model is able to accurately predict future states such as calving, mastitis, pregnancy and death. The framework presented in this research can be used to enhance current animal monitoring systems with better animal welfare and higher financial returns for the farmer as a result.

Keywords: Deep learning, sequence classification, animal monitoring, computer vision, Markov for discrimination

Introduction

As a major livestock producer, the EU is directly affected by the global need for more sustainable food production (Gerber *et al.,* 2013). The common currency in developing solutions to all of these challenges is improved animal production efficiency (Beukes *et al.,* 2010; Beauchemin *et al.,* 2008; VandeHaar & St-Pierre, 2006). In particular, the use of precision livestock farming (PLF) technologies for genetic selection and early disease detection has shown a lot of promise (Rutten *et al.*, 2013; Banhazi *et al.,* 2012; Berckmans, 2014). In this study, we contribute to the literature by showing how systematically recording fertility and disease events can indeed be helpful in improving existing animal monitoring systems. We propose a multiclass model which forecasts a probability distribution over 12 possible life events. More specifically, we show how traditional techniques such as Markov for discrimination models can use historical sequences of disease and fertility records in order to predict a cow's future state. Additionally, we investigate whether more advanced recurrent neural network algorithms are better able to uncover the complex data patterns hidden in the event sequences. Finally, we examine if augmenting a cow's history of events with pictures can enhance the predictive performance even further by making use of convolutional neural network models. The use of pictorial information in animal health analysis has been used before in order to predict body condition scores (Halachmi *et al.,* 2013; Alvarez *et al.*, 2018), detect lameness (Poursaberi *et al.,* 2010; Zhao *et al.*, 2018) and mastitis (Berry *et al.*, 2003). While most of these studies were conducted as experimental designs and made use of complex video camera setups and expensive equipment such as thermal scanners, we worked with pictures taken by the farmers with their smartphones, which to our most recent knowledge, has not yet been applied in the context of animal monitoring systems.

Materials and methods

Data

The raw data was collected from an online platform, built for farmers to store, monitor and analyse data on their livestock (www.mmmooogle.com). More specifically, the platform allows farmers to map the evolution of a cow's life by systematically recording its current life condition, optionally accompanied by one or more pictures taken from the cow. In total, we collected 222,756 recordings of 22 unique events from 49,671 different cows coming from six different herds. For 26,903 of these events, one or more pictures were available. The aggregated data consisted of a collection of timelines of events and pictures for each cow that was registered on this platform.

The data used in this study consisted of a collection of timelines of events, with some events accompanied by one or more pictures. In order to predict the next event, a model could be trained to find a relationship between the sequence's last occurring event and all the previous ones, and deploy it on new unseen sequences. The problem with this approach, however, is that if the sequence lengths differ such as in this study, it will not be possible to train such a model, since several observations would have a different number of predictors. This was handled by making use of a sliding window.

One problem that often arises with classification tasks is class imbalance, where some classes severely out represent the others (Garcia & He, 2009). This can drive models to become biased towards the large classes and ignoring the smaller ones (Chawla *et al.*, 2004). One particular set of techniques that has often been found to be very effective in coping with this problem, are sampling methods (Laurikkala, 2001; Weiss & Provost, 2001; Estabrooks *et al.*, 2004). These techniques modify the data such that the data distribution eventually becomes balanced. This study used random up-sampling, which augments each minority class by randomly sampling observations from their own distribution, until they are as large as the majority class (Garcia & He, 2009).

Modelling

The goal of the research is to predict the next life event of a cow given its history of events as well as pictorial information. Figure 1 describes the data preprocessing stage including a Markov discrimination model, a recurrent and convolutional neural network model. These models were trained on the sequential data of events as well as the pictorial information to estimate the class posterior distribution. Additionally, ensembles of the aforementioned models and different evaluation criteria were used for model assessment and selection.

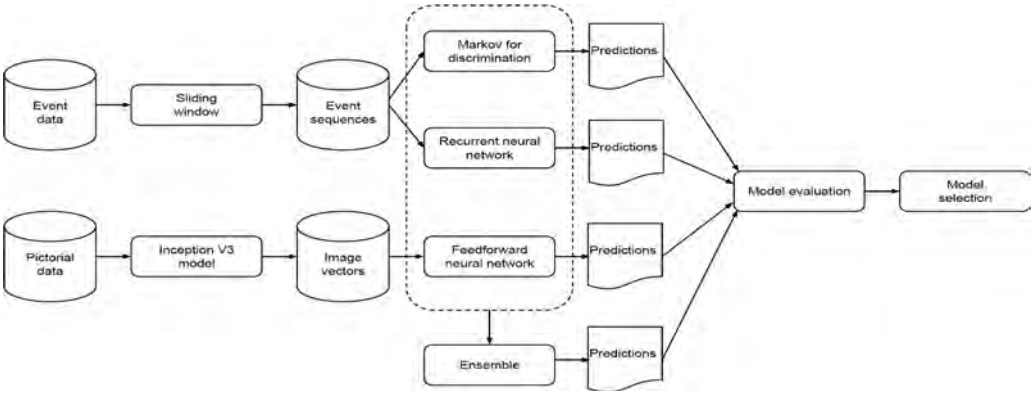

Figure 1. Schematic overview of the methodology used in this study

To compare the predictive performance of the different models, we utilised three evaluation measures: accuracy or Percentage Correctly Classified (PCC), weighted accuracy (wPCC) and the top-3 accuracy (Top-3 PCC).

Results

First of all, we found that the Long Short Term-Memory (LSTM) recurrent network model trained on the imbalanced dataset outperformed all other models in terms of PCC and Top-3 PCC. While the Markov for discrimination models MFD-1 and MFD-2 their PCC and Top-3 PCC ranged from 67% to 68% and from 87% to 88% respectively, the LSTM achieved a PCC of 75% and a Top-3 PCC of 95%. By balancing the dataset, the LSTM achieved a much lower PCC of 60%, but increased the wPCC from 42% to 58%, the highest value achieved among the stand-alone models. This clearly indicates how balancing the data improved the model's performance in identifying the smaller classes. The ensemble of both LSTMs achieved a PCC, wPCC and Top-3 PCC of 73%, 51% and 94%, exceeding both MFD models and their ensemble in all evaluation metrics. Hence, these results suggest that recurrent neural network models are better able to uncover the complex relationship between a cow's historical sequence of events and its future state.

The sequential data of fertility and health records contained more predictive power towards a cow's subsequent state than the models solely trained on pictorial information. However, we saw that the CNN trained on the balanced dataset was particularly good at identifying mastitis, with a class specific PCC of 59%. On top, we observed that the CNN model trained on the balanced dataset was among the best models in identifying impending death, with an accuracy of 97%. The CNN's good performance in identifying diseases and animal death could be explained by the fact that farmers may be more likely to take a large number of high quality pictures in case of pending animal disease or death than during more trivial situations. Hence, these results show that augmenting historical sequence data with pictorial information can be beneficial for predicting the animal's subsequent life event.

Discussion

The main objective of this study was to provide a framework which could be used to enhance current animal monitoring practices. While previous research primarily applied specialized and expensive equipment for its data collection such as AMS, sensors and thermal scanners, our framework made use of rather cheap data sources. More specifically, we used fertility and disease records as well as pictures taken with a smartphone, all being registered by the farmer on an online and user-friendly platform. Moreover, while other studies primarily focused on predicting binary outcomes such as having mastitis or not, in this study a multiclass classification algorithm is presented, which predicts a probability distribution over 12 different life events of a cow. These algorithms are in general much harder to train since these must model multiple decision boundaries and require more data observations. The results discussed showed that the ensemble of the LSTM and CNN trained on sequential as well as pictorial information performed best (Table 1).

Table 1. Final model results on test set summarized by PCC, wPCC and Top-3 PCC

Model	Dataset	PCC	wPCC	Top-3PCC
LSTM & CNN	Balanced	0.58	0.46	0.88

The results in Figure 2 show that the final model was able to identify mastitis as the cow's next life event with 68% accuracy. Accurate mastitis detection is currently one of the most crucial monitoring tasks found on dairy farms. Nevertheless, current mastitis detection systems still do not perform well enough to be applied in practice according to many authors (Hogeveen *et al.*, 2010; Jensen *et al.*, 2016; Martin *et al.*, 2018). It has been suggested though that a combination of different data source would be beneficial for mastitis detection systems, as the disease is associated with many changes in the cow as well as in the milk (Hogeveen *et al.*, 2010; Hogeveen, 2005). This was also illustrated in this study, where we showed that both the historical sequences of life events and the pictorial information explained distinct factors of variation of mastitis. Hence, augmenting the production data used in previous research with the data proposed in this study could help to improve current mastitis detection performances, as it would provide a more complete set of indicators for the disease.

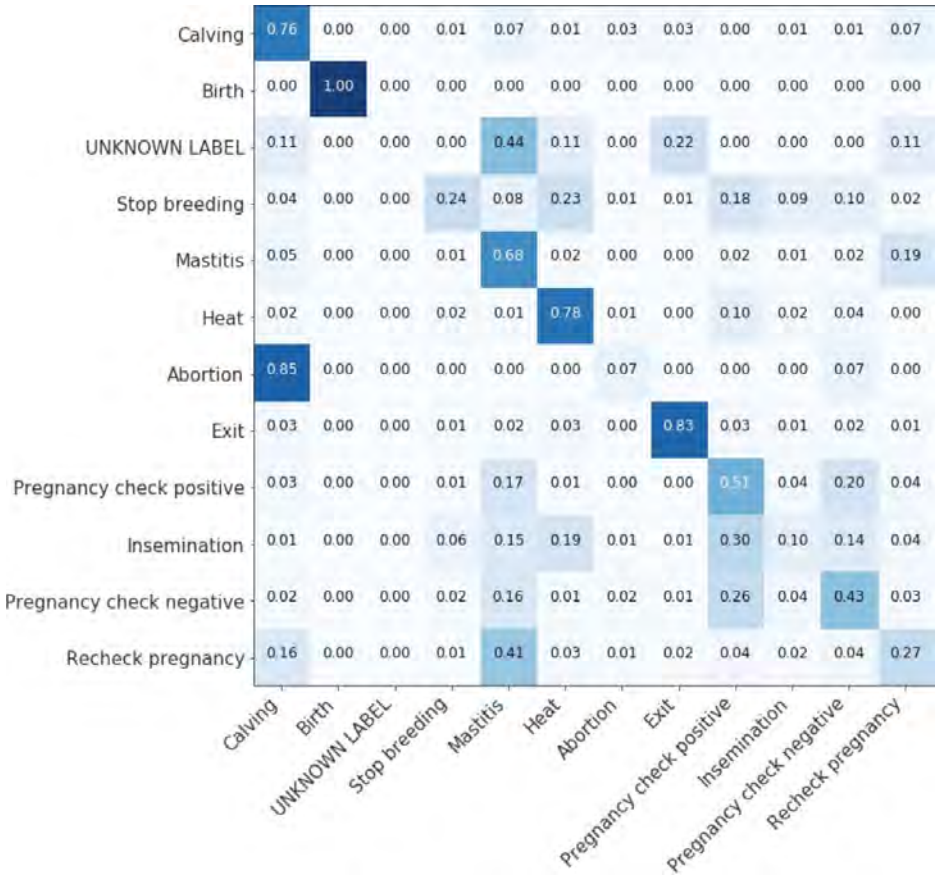

Figure 2. Confusion matrix of the final model on the test set with the true labels on the Y-axis and the predicted labels on the X-axis

In addition to that, we were able to predict the culling or death of an animal, as indicated by exit, with 83% accuracy. Modeling the optimal moment to cull animals has been an emerging topic over the last decade, as it is important for managing dairy production response and profitability. Too frequent culling results in excessive replacement expenditures, while too slow culling may cause milk production, reproduction or genetic improvement to become

impaired (Hadley *et al.,* 2006). The model presented in this research, however, predicts the probability of a cow being replaced, whether it is voluntary or not. As such, these predictions could be incorporated in current optimization frameworks and enhance culling strategies. At the same time, they could help to alert farmers and farm collaborators for pending culling or death events, which could motivate preventive measures to be taken.

Finally, it should be noted that although most other studies made use of data records extracted from AMS and sensors, most farmers today don't have access to these automated monitoring systems. In particular, it was estimated that by 2014 only 5% of Canadian dairy farms had installed AMS, while in Europe the largest adoption rate was found in Denmark, with 24% of the farmers making use of this technology (Barkema *et al.,* 2015). The low adoption rate of these monitoring systems may include the high installation cost, the farmer's uncertainty about applying the new technologies and the risks and costs associated with maintenance (Jacobs & Siegford, 2012; De Koning & Rodenburg, 2004). Hence, a lot of livestock producers still have insufficient data to produce satisfactory data-driven decision making. The framework presented in this study, however, could facilitate the collection of data records, as it is based on a cheap and user-friendly software platform. Moreover, given the final model's Top-3 accuracy of 88%, a farmer could quite accurately be provided with a cow's three most likely subsequent states. Together with the farmer's personal experience, this could facilitate a more accurate, consistent and standardized documentation of a cow's history of events, which in turn provides the opportunity to improve animal monitoring.

Conclusion

In this study, we showed how consistently recording fertility and disease events as well as pictures can be used for predicting a cow's subsequent life event. More specifically, we illustrated how traditional sequence models such as MFD can predict a cow's future state based on its history of recorded events. Moreover, we found how recurrent neural network models can be exploited to uncover these complex data patterns with higher accuracy. Nonetheless, the best performance was yielded by combining a LSTM and CNN model trained on sequential as well as pictorial information. Hence, the results obtained in this research not only confirm the need for a more standardized data input of fertility and disease events, they also show how other non-production data sources such as pictures could improve current animal monitoring systems even more, which may in turn lead to improved decision making for optimal herd management.

References

Alvarez, J.R., Arroqui, M., Mangudo, P., Toloza, J., Jatip, D., Rodr´ıguez, J.M., Teyseyre, A., Sanz, C., Zunino, A., Machado, C., & Mateos, C. (2018). Body condition estimation on cows from depth images using convolutional neural networks. *Computers and Electronics in Agriculture*, 155: 12–22.

Banhazi, T.M., Lehr, H., Black, J., Crabtree, H., Schofield, P., Tscharke, M., & Berckmans, D. (2012). Precision livestock farming: an international review of scientific and commercial aspects. *International Journal of Agricultural and Biological Engineering*, *5:* 1–9.

Barkema, H., von Keyserlingk, M., Kastelic, J., Lam, T., Luby, C., Roy, J.-P., LeBlanc, S., Keefe, G., & Kelton, D. (2015). Invited review: Changes in the dairy industry affecting dairy cattle health and welfare. *Journal of Dairy Science*, *98:* 7426–7445.

Beauchemin, K., Kreuzer, M., O'mara, F., & McAllister, T. (2008). Nutritional management for enteric methane abatement: a review. *Australian Journal of Experimental Agriculture*, 48: 21–27.

Berckmans, D. (2014). Precision livestock farming technologies for welfare management in intensive livestock systems. *Scientific and Technical Review of the Office International des Epizooties*, 33: 189–196.

Berry, R., Kennedy, A., Scott, S., Kyle, B., & Schaefer, A. (2003). Daily variation in the udder surface temperature of dairy cows measured by infrared thermography: Potential for mastitis detection. *Canadian Journal of Animal Science*, 83: 687–693.

Beukes, P., Gregorini, P., Romera, A., Levy, G., & Waghorn, G. (2010). Improving production efficiency as a strategy to mitigate greenhouse gas emissions on pastoral dairy farms in New Zealand. *Agri culture, Ecosystems and Environment*, 136: 358–365.

Chawla, N.V., Japkowicz, N., & Kotcz, A. (2004). Editorial: Special issue on learning from imbalanced data sets. *ACM SIGKDD Explorations Newsletter, 6:* 1–6.

De Koning, K., & Rodenburg, J. (2004). Automatic milking: State of the art in Europe and North America. *Automatic Milking, A Better Understanding*, 27–37.

Estabrooks, A., Jo, T., & Japkowicz, N. (2004). A multiple resampling method for learning from imbalanced data sets. *Computational Intelligence*, 20 : 18–36.

Garcia, E.A., & He, H. (2009). Learning from imbalanced data. *IEEE Transactions on Knowledge and Data Engineering*, 21: 1263–1284.

Gerber, P.J., Steinfeld, H., Henderson, B., Mottet, A., Opio, C., Dijkman, J., Falcucci, A., & Tempio, G. (2013). *Tackling climate change through livestock: a global assessment of emissions and mitigation opportunities*. Food and Agriculture Organization of the United Nations (FAO).

Hadley, G., Wolf, C., & Harsh, S. (2006). Dairy cattle culling patterns, explanations, and implications. *Journal of Dairy Science*, 89: 2286–2296.

Halachmi, I., Klopˇciˇc, M., Polak, P., Roberts, D., & Bewley, J. (2013). Automatic assessment of dairy cattle body condition score using thermal imaging. *Computers and Electronics in Agriculture*, 99: 35–40.

Hogeveen, H. (2005). Mastitis in Dairy Production: Current knowledge and future solutions. Wageningen Academic Publishers.

Hogeveen, H., Kamphuis, C., Steeneveld, W., & Mollenhorst, H. (2010). Sensors and clinical mastitis, the quest for the perfect alert. *Sensors*, 10: 7991–8009.

Jacobs, J., & Siegford, J. (2012). Invited review: The impact of automatic milking systems on dairy cow management, behavior, health, and welfare. *Journal of Dairy Science*, 95: 2227–2247.

Jensen, D.B., Hogeveen, H., & Vries, A.D. (2016). Bayesian integration of sensor information and a multivariate dynamic linear model for prediction of dairy cow mastitis. *Journal of Dairy Science*, 99: 7344–7361.

Laurikkala, J. (2001). Improving identification of difficult small classes by balancing class distribution. In *Artificial Intelligence in Medicine* (pp. 63-66). Springer Berlin Heidelberg.

Martin, P., Barkema, H., Brito, L., Narayana, S., & Miglior, F. (2018). Symposium review: Novel strategies to genetically improve mastitis resistance in dairy cattle. *Journal of Dairy Science*, 101: 2724–2736.

Poursaberi, A., Bahr, C., Pluk, A., Nuffel, A.V., & Berckmans, D. (2010). Real-time automatic lameness detection based on back posture extraction in dairy cattle: Shape analysis of cow within age processing techniques. *Computers and Electronics in Agriculture*, 74: 110–119.

Rutten, C., Velthuis, A., Steeneveld, W., & Hogeveen, H. (2013). Invited review: Sensors to support health management on dairy farms. *Journal of Dairy Science*, 96: 1928–1952.

VandeHaar, M., & St-Pierre, N. (2006). Major advances in nutrition: Relevance to the sustainability of the dairy industry. *Journal of Dairy Science*, 89: 1280–1291.

Weiss, G.M., & Provost, F. (2001). *The effect of class distribution on classifier learning: an empirical study*. Technical Report ML-TR-44 Department of Computer Science, Rutgers University.

Zhao, K., Bewley, J., He, D., & Jin, X. (2018). Automatic lameness detection in dairy cattle based on leg swing analysis with an image processing technique. *Computers and Electronics in Agriculture*, 148: 226–236.

Providing real-time access to the ICBF database using RESTful APIs

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Abstract

There have been many changes in technologies in recent years which have increased the sources of data available. Examples of this would include the smart phone, robotics, artificial intelligence, Internet of Things (IoT) devices and sensors.

As a result, ICBF has been actively developing a series of APIs to exchange data with third party devices and applications, and in particular, an API is being developed to make it easy for the Irish farmer to access and record data on their animals through these devices.

The ICBF Herd APIs are a suite of RESTful (Representational state transfer) services available to software and sensor providers that allows data to be exchanged with the ICBF database and enhance the data services available to farmers.

The services available include the details of animals on the farm; milking recording, fertility, weight and health data, as well as genetic and genomic evaluation data. These services can be used by tools which help with on-farm decision-making and make it easier to record data the animals.

Keywords: API, REST, IoT, database, web services, genetic evaluation, data recording

Introduction

The Irish Cattle Breeding Federation (ICBF) was formally set up in 1998, and is a non-profit organisation charged with providing cattle breeding information services to the Irish dairy and beef industries. ICBF applies science and technology to ensure that farmers and industry make the most profitable and sustainable decisions, through the use of the services provided from the ICBF cattle breeding database.

These services include the ICBF Herd APIs, which are a set of web services available to software and sensor providers to provide data services to farmers. They are built using REST (Representational state transfer) and JSON (JavaScript Object Notation).

Web Services

ICBF has made available a comprehensive set of RESTful services which expose herd related data that can be used by software providers to enhance the features they provide and to send data to the national cattle breeding database. Access to the services are controlled by making them available under various scopes, providing access to each scope only as required.

RESTful API Structure

ICBF uses a PHP based API builder called Apigility (https://apigility.org) which simplifies the creation and maintenance of useful, easy to consume and well-structured APIs. Apigility structures the services according to the Hypertext Application Language (M Kelly, 2011) specification which readily achieves the Richardson Maturity Model Level 3 (M Fowler, 2010). This ensures that each resource contains relational links, and that a standard, identifiable structure for embedding other resources is used. See Figure 1 for an example.

Request:

```
GET /v2/herd-fertility/insemination?animal_id=IE123456760549 HTTP/1.1
Host: apitest.dev64.icbf.com
Accept: application/json
Authorization: Bearer c68faab0cb81b71f70c6552dbedaf2802517668e
Cache-Control: no-cache
```

Response:


```
{
  "_links": {
      "self": {
         "href": "/v2/herd-fertility/insemination?animal_id=IE123456760549&page=1"
      },
      "first": {
         "href": "/v2/herd-fertility/insemination?animal_id=IE123456760549"
      },
      "last": {
         "href": "/v2/herd-fertility/insemination?animal_id=IE123456760549&page=1"
      }
   }, "_embedded": {
      "insemination": [
         {
            "id": "12334",
            "animal_id": "IE123456760549",
            "activity_date": "19-NOV-14"
            "editable": "UD",
            "_links": {
               "self": {
                  "href": “/v2/herd-fertility/insemination/12334"
               }
            }
         }
      ]
   },
   "page_count": 1,
   "page_size": 100,
   "total_items": 1,
   "page": 1
}
```


Figure 1. Example of a request for insemination data of a given animal

The services available are summarised in Table 1. Most of services provided allow the user to read, create, update and delete data in real-time. It is possible filter the data returned from the read requests in order to limit what is returned. The filters available typically consist of one of the following: start date, animal identifier or the ID of the resource.

The start date filter will limit the data returned to only records recorded or changed since that date. The animal identifier filter will return all data recorded on that animal for that service and the if the ID is provided; the service will only return that record.

Table 1. Overview of Herd APIs currently available from ICBF

Scope	Service	Methods available	Description
Herd Details	Animal Details	Read	The animals currently in the herd and their details such as birth date, sex, breed, arrival date, etc.
	Purpose	Read | Update	The purpose of the animal, either beef or dairy, which is typically calculated using criteria such as the breed of the animal.
	Culling	Read | Write | Update | Delete	Animals that have been marked for culling are available with this service. The reason for the culling must also be provided.
Herd Fertility	Heat	Read | Write | Update | Delete	The heat data recorded on animals in the herd.
	Inseminations	Read | Write | Update | Delete	The insemination data recorded on animals in the herd. This includes data that are recorded by AI technicians using ICBF's handheld system.
	Pregnancy Diagnosis	Read | Write | Update | Delete	Data detailing whether an animal is pregnant, empty or pregnant with twins. Optionally, days in calf can be included.
	Expected Calving	Read	Based on the available insemination and pregnancy diagnosis data, predications are made on the expected calving date of the animal.
Herd Evaluations	Beef	Read	The beef evaluations of animals in the herd, e.g. maternal and terminal indexes etc.
	Dairy	Read	The dairy evaluations of animals in the herd, e.g. EBI, milk and fertility indexes
Herd Weight	Live Weight	Read | Write | Update | Delete	The weight data recorded on the animals in the herd. Where the data has been provided by a mart, the price paid can also be included.
Herd Health	General Health	Read | Write | Update | Delete	Illnesses and other health issues recorded against the animals. With mastitis and lameness, the quarter affected is also recorded.
Herd Lactation	Period	Read | Write | Update | Delete	Lactation / calving data recorded on the animals in the herd, including milk recording information. Dry off dates can be recorded and updated. The treatment used to dry off an animal can also be included.
Herd Survey	Animal	Read | Write | Update | Delete	Surveys on animals typically need to be completed as part of Department of Agriculture schemes such as the Beef Data and Genomics Programme (BDGP). This service allows for the recording of many surveys on animals such as calving ease score, cow and bull docility.

Authorisation and Authentication

Authorisation and Authentication with the API is handled using oAuth 2.0 which is an industry standard protocol for authorisation. OAuth 2.0 focuses on client developer simplicity while providing specific authorisation flows for web applications, desktop applications, mobile phones and other devices (oauth.net/2).

A particularly important advantage of using oAuth 2.0 is that it keeps the farmer's authorisation details away from the client devices which are typically considered to be insecure. It does this with a series of unique token exchanges. This ensures that if the client device becomes compromised, the farmer's authorisation details are still safe.

The farmer has full control of what organisations have access to their data through an authorisation web portal available on www.icbf.com.

Conclusions

The suite of API's made available by ICBF allows for the sharing and recording of farmer recorded data across many software solutions and devices. These APIs have many wide-ranging advantages for the agricultural industry, greatly enhancing the features that can be provided. The data collected and shared increases the accuracy of genetic evaluations which leads to breeding more profitable cattle.

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References

M. Fowler. (2010). *Richardson Maturity Model*. https://martinfowler.com/articles/richardsonMaturityModel.html.

M. Kelly. (2011). *HAL - Hypertext Application Language*. http://stateless.co/hal_specification.html.

Department of Agriculture, Food and Marine, (2015). *Terms and Conditions of the Beef Data and Genomics Programme (BDGP)*. https://www.agriculture.gov.ie/media/migration/farmingschemesandpayments/beefdataprogrammebdp/2015/BDGP050515.pdf.

Session 9

Performance and Welfare of Dairy Animals (1)

Social acceptance of digital livestock farming technologies: the dairy sector

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Abstract

Although social acceptance of digital farming technologies is of paramount importance, very little research has been conducted in this area so far. An online survey in Germany provides first results. The composition of the pre-quoted sample (n = 2,012) is representative of the population living in Germany in terms of gender, age, size of place of residence, and education. In addition to the relation with, knowledge of, and general attitude and perception of agriculture in Germany, the acceptance of digital farming technologies, including sensors for livestock farming, was inquired. First, the rating of statements was conducted on a very general level. Then, respondents were queried on their opinions on the use of sensors for livestock farming and on public financial support as a means to foster their adoption. In the last part of the online survey, respondents were asked for their spontaneous associations with pictures showing digital farming technologies for animal husbandry. In their general attitude toward digital farming technologies, respondents are mostly positive. The approval of the use of sensors for livestock farming and even the consent for public funding of famers using these sensors is high. When confronted with pictures of digital technologies for dairy farming (e.g. milking robot), however, the emotional component becomes apparent, which partly results in negative statements by respondents.

Keywords: social acceptance, dairy farming, digital farming technologies, survey

Introduction

Agriculture has made great progress in terms of digitalisation, which contributed to overall increased efficiency (e.g. Bos *et al.*, 2003). However, although society sees many positive aspects of modern agriculture today (as indicated for the Dutch population by Boogaard *et al.,* 2008), it also has negative connotations (Boogaard *et al.*, 2011b). Modern animal husbandry and progressive forms of agriculture are often criticised by society, partly for leading to a loss of values and traditions (Scott, 2006). Therefore, consumers and society as a whole are increasingly paying attention to agricultural production, resulting in growing social expectations regarding animal welfare and environmental protection. A general opinion in the sector confirms that digital farming technologies (DFT) can make a valuable contribution to dealing with these issues.

Although social acceptance of digital farming technologies is of paramount importance, very little research has been conducted in this area so far. In many cases, the economic and environmental impacts of technologies and production processes are analysed, but the social component is neglected (Boogaard *et al.*, 2011b). However, this would be relevant because agriculture certainly presents an area of tension. Studies have also proven that society has concerns about modern livestock practices (e.g. Boogaard *et al.*, 2011b). However, many studies on social acceptance focus on single aspects such as animal welfare (e.g. Deemer & Lobao, 2011; Kendall *et al.,* 2006).

Therefore, the aim of the present study is to gain a deeper understanding of society's acceptance and attitudes toward digitalisation in agriculture in Germany. Therefore, we pose the following questions: (1) What is the attitude of society toward the use of digital

technologies in agriculture? (2) To what extent is there an agreement to provide farmers with public funding to foster the dissemination of these technologies in practice? (3) Which factors explain differences in response behaviour and thus acceptance of digitalisation? (4) What concerns does the population have regarding digital technologies in dairy farming in particular?

Materials and methods

The data necessary to answer these research objectives was obtained through an online survey. A set of questions was elaborated to answer the relevant research questions of the study. The composition of the pre-quoted sample (n = 2,012) is representative of the population (18 years and older) living in Germany in terms of gender, age, size of place of residence, and education. First, Likert scales were used to determine the respondents' relationship with, and knowledge of, agriculture and its production processes in Germany. Furthermore, the general attitude and perception of agriculture in Germany were questioned. The survey participants were then introduced to a number of digital farming technologies, their functions, and their potential for more sustainable production. The rating of statements was conducted on a very general level but in some cases also addressed specific technology, including sensors for livestock farming. With regard to the sensors for livestock farming, the survey was directed to single-animal sensors for attachment to the animal to monitor appropriate parameters such as behaviour (e.g. activity). Based on this, the respondents were queried about their opinions on the use thereof and on public investment subsidies as a means to foster their adoption (as will be the case in Bavaria, Germany). In the last part of the online survey, respondents were asked for their spontaneous associations with pictures showing digital farming technologies for animal husbandry. The pictures showed a cow during the milking process in a milking robot and a feeding robot feeding cows in a barn, respectively. For each of the two presented pictures, the respondents could state up to three spontaneous associations. They were not given any additional information about the respective pictures of DFT. The stated spontaneous associations of the respondents were intended to shed light on motivations and concerns in society. In particular, negative connotations can help identify reasons for a lack of acceptance of these technologies. For each of the pictures, all entries suitable for evaluation were grouped into categories with similar terms and thoughts. As far as possible, we consistently used the same categories for both pictures and assigned them a connotation.

Results

With regard to their relationship with agriculture, 8% of survey respondents state that they have some working experience in the agricultural sector, while 92% have none. In total, 33% indicate that they have personal contact with at least one farmer, with whom 19% also talk about agricultural issues; for the remaining 14%, agriculture is not a topic of conversation.

Respondents rate their knowledge about present-day agriculture itself as mediocre to rather low. In particular, the self-assessment questions cover their knowledge about crop production, animal husbandry processes, and the latest machinery and equipment used in agriculture. Nevertheless, for all three items, a higher share of respondents indicate that they have very good or good knowledge about present-day agriculture (13% and 20%, respectively) with only (8%) indicating that they have working experience in agriculture (8%).

The general attitude of the survey participants toward agriculture is quite positive, and values linked to agriculture also seem to play a relevant role. On average, respondents

indicate that they have a generally positive attitude toward agriculture in Germany. Family farm structures, preservation of the environment for future generations, and farm animals welfare are most valuable and relevant to them. Related to this, respondents prefer organic products to conventionally produced products on average. A high number of respondents agree that farmers should have more free time and combine modern technology with positive feelings.

The general perception of agriculture in Germany is rated less distinctively by the respondents than the general attitude toward agriculture. The agreement that German farmers pay great attention to the welfare of their animals and protect the environment is modest in both cases. Similarly, there is low agreement that the image of German agriculture in the media is too negative. For all of these three items, a high proportion of undecided respondents (43–45%) emerged.

General attitude toward the benefits of digital farming technologies

In their general attitude toward DFT, respondents are mostly positive (see Figure 1). A majority of respondents sees the benefits of using DFT primarily as an improvement in the quality of life for the farming family (74% totally agree or rather agree). Furthermore, they also see the potential to enable more environmentally friendly production (62% of them totally agree or rather agree) and improve animal welfare and animal health (56% totally agree or rather agree). The survey participants' agreement that DFT bring consumers and farmers closer together is only moderate (36% totally agree or rather agree). Respondents' opinions are differentiated concerning the question of whether DFT leads to alienation of the farmer from his soil and animals. It should be noted in this context that a relatively high share of undecided respondents (between 23 and 44%) are found for all of the items in this category.

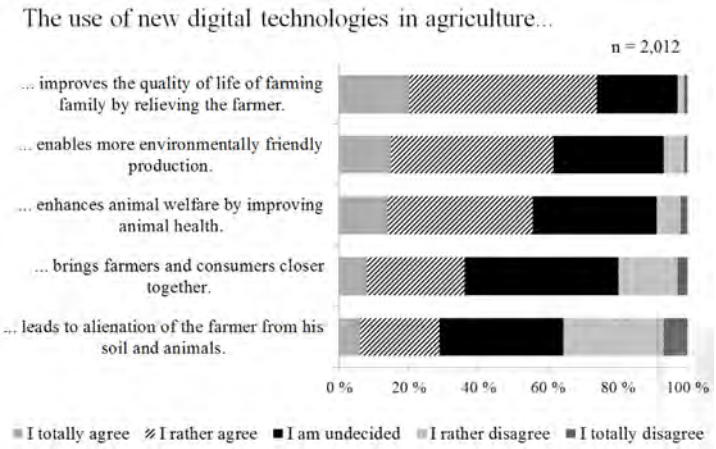

Figure 1. General attitude toward the benefits of digital farming technologies

Support of technology use and consent to public funding of sensors for livestock farming

The approval of the use of sensors in livestock farming is very high, with 77% of the respondents fully agreeing or rather agreeing. In addition, the consent to public funding of farmers using sensors for livestock farming is also high (66% totally agree or rather agree). However, there is a high share of undecided survey respondents in both items (20 and 25%, respectively) (see Figure 2).

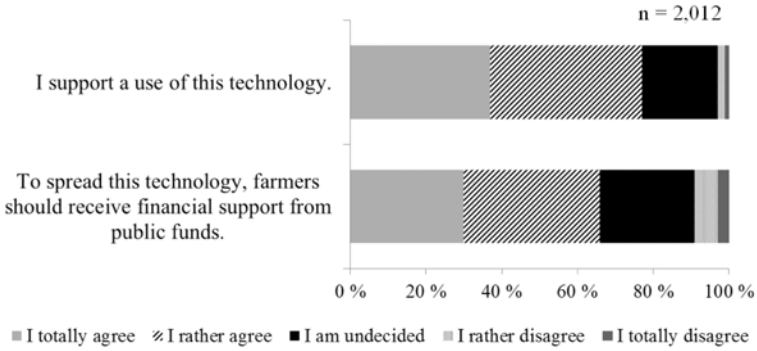

Figure 2. Support of technology use and consent to public funding of sensors for livestock farming

Both general attitudes of the population in Germany toward DFT and the specific case of sensors for livestock farming show that socio-demographic factors and the relationship with agriculture had little or no impact on how the questions were answered. This applies equally to the level of knowledge about present-day agriculture and its production processes. Rather, it becomes clear that the consent to DFT technologies (including sensors for livestock farming) is higher among respondents whose general attitudes to agriculture are more positive (among other things, animal welfare and environmental protection are considered to be very relevant and modern technology is combined with positive feelings). Likewise, respondents who had a stronger trust in or a more positive perception of agriculture in Germany had a more positive attitude toward DFT in general as well as a higher acceptance of sensor use in livestock farming.

Spontaneous associations

For the most part, the spontaneous associations in response to the pictures of the milking and feeding robot, respectively, could be grouped into similar categories. In both pictures, terms belonging to the categories *technology, automation, robotics,* and *digitalisation* were mentioned. Furthermore, many general terms related to *dairy farming*, but also to *milking* and *feeding* were associated with the pictures. Many respondents perceived the two technologies as 'innovative' and 'futuristic', from which the rather positively rated category *future and progress* was derived. One of the most frequently mentioned categories is *reduced workload and efficiency* by means of DFT. In this context, respondents associated terms were used such as 'effective', 'fast', and 'higher precision' of agriculture (for example, in the distribution of feed in the barn). However, a 'loss of jobs' was also mentioned several times in this category. The issue of *industrial agriculture* plays a relevant role in both of the two presented dairy farming technologies. In this regard, respondents were worried, for example, about 'exploitation of the animals', 'alienation' (in terms of 'impersonal', 'no relation to the animal'), 'factory farming', and 'animal as a matter'. Terms concerning to *animal cruelty* are frequently found with the picture of the milking robot. For example, 'animal suffering', 'tight', 'poor cow', 'not animal-friendly' and 'imprisoned' are among the terms used in this category. In general, both pictures had a high share of negatively rated spontaneous associations.

Discussion

The surplus of positive attitudes of the survey participants toward agriculture in Germany found in this study confirms the findings of other studies (Köcher, 2009; Helmle, 2011; Kantar EMNID, 2017). Furthermore, it turns out that the general attitude of the respondents toward digitalisation in agriculture is mostly positive. Due to the high relevance of animal

welfare and environmental protection in society, DFT that can contribute to these issues are highly accepted. The active agreement of the survey participants to public funding for livestock sensors as a means to foster their adoption confirms this as well. The welfare of animals is given high priority not only in this survey but also in other studies (Boogaard *et al.,* 2011b; Macnaghten, 2004; Köcher, 2009).

According to our findings, accepting digital technologies in agriculture and agreeing to their funding is based on a good general attitude toward farming, while positive perception and trust in agriculture are decisive influencing factors. It is based on values and beliefs that shape peoples' attitudes and decisions, including agricultural issues (Boogaard *et al.*, 2011a; Manski, 2004; Lusk *et al.*, 2014).

Agriculture is perceived by society as an innovative sector (Boogaard *et al.*, 2008). The spontaneous associations confirm that the addressed digital technologies for dairy farming are considered by many people to be innovative and relevant to the future. Nevertheless, society's attitude toward modern agriculture, including modern animal farming, is ambivalent (Boogaard *et al.*, 2011a), as it also creates many negative impressions in society. Modern technologies for dairy farming, for example, are connoted negatively with animal welfare and the idea of industrial agriculture, as was revealed by a high number of negative associations with the presented pictures thereof, especially the loss of naturalness and tradition as a function of modernity in livestock raises concerns (e.g. Boogaard *et al.*, 2011a). A high number of general terms of modern dairy farming in the spontaneous associations also show that criticism is not necessarily related to digital technologies but rather to the general forms of modern dairy husbandry. For example, barn housing is criticised as opposed to grazing and also the preservation of family farms is an important aspect for society and thus often addressed (e.g. Boogaard *et al.,* 2011a).

In order to increase the social acceptance of digital technologies in agriculture, one approach could be to provide society with objective information on the need for DFT and their potential for more sustainable production processes. However, it is not only the knowledge of the population that is decisive since a higher level of knowledge does not necessarily lead to higher social acceptance (see also e.g. Wuepper *et al.,* 2018). Rather, building trust between consumers and farmers, for example through direct contact, is necessary for a more positive perception of agriculture in society and therefore can lead more easily to a higher acceptance of new applied DFT.

Conclusions

The results of the survey confirm that the German population has increasingly moved away from agriculture and that society is less aware of the current agricultural production processes. If the potential of digital technologies in terms of animal welfare is explained, respondents react favorably to modern digital technologies. When confronted with pictures of digital technologies for dairy farming, however, the emotional component becomes apparent, which in part results in negative statements by respondents. One approach to increase social acceptance of (digital) dairy farming lies therefore in providing society with neutral information on digital farming technologies, on the one hand, and in building trust between consumers and farmers, on the other hand.

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References

Bos, B., Groot Koerkamp, P.W.G. and Groenestein, K. (2003). A novel design approach for livestock housing based on recursive contro - with examples to reduce environmental pollution. *Livestock Production Science,* 84: 157–170.

Boogaard, B.K., Oosting, S.J. and Bock, B.B. (2008). Defining sustainability as a socio-cultural concept: Citizen panels visiting dairy farms in the Netherlands. *Livestock Science,* 117: 24–33.

Boogaard, B.K., Bock, B.B., Oosting, S.J., Wiskerke, J.S.C. and Van der Zijpp, A.J. (2011a). Social acceptance of dairy farming: the ambivalence between the two faces of modernity. *Journal of Agricultural and Environmental Ethics,* 24: 259–282.

Boogaard, B.K., Oosting, S.J., Bock, B.B. and Wiskerke, J.S.C. (2011b). The sociocultural sustainability of livestock farming: an inquiry into social perceptions of dairy farming. *Animal,* 5: 1458–1466.

Deemer, D.R. and L.M. Lobao (2011). Public concern with farm-animal welfare: religion, politics, and human disadvantage in the food sector. *Rural Sociology*, 76: 167–196.

Helmle, S. (2011). Darf es heute etwas Landwirtschaft sein? Über das Image der Landwirtschaft in Deutschland. *Journal of Socio-Economics in Agriculture*, 4: 35–38.

Kantar EMNID (2017). Das Image der deutschen Landwirtschaft. https://media.repro-mayr.de/79/668279.pdf. Accessed on 01.03.2019.

Lusk, J.L., Schroeder, T.C. and Tonsor, G.T. (2014). Distinguishing beliefs from preferences in food choice. *European Review of Agricultural Economics,* 41: 627–655.

Macnaghten P (2004). Animals in their nature: A case study on public attitudes to animals, genetic modification and 'nature'. *Sociology,* 38: 533–551.

Manski, C.F. (2004). Measuring expectations. *Econometrica*, 1329–1376.

Kendall, H.A., Lobao, L.M. and Sharp, J.S. (2006). Public concern with animal well-being: Place, social structural location, and individual experience. *Rural Sociology,* 71: 399–428.

Köcher, R. (2009). Landwirtschaft und Gesellschaft. Einstellungen, Erwartungen, Erfahrungsund. Fernbild – Ergebnisse einer aktuellen Befragung. In: DLG e. V. (ed) *Landwirtschaft. (2020). Herausforderungen, Strategien, Verantwortung*, DLG Verlag, Frankfurt am Main, Germany, 227–248.

Scott, J. (2006). *Sociology: The key concepts*, Routledge, London.

Wuepper, D., Wree, P. and Ardali, G. (2019). Does information change German consumers' attitudes about genetically modified food? *European Review of Agricultural Economics,* 46: 53–78.

Interactive comparison tool for management of reproduction based on pregnancy rate

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Abstract

The overall objective of this study was to improve the reproductive efficiency of lactating dairy cows and to improve the resulting total farm profit. The hypothesis is that a dairy farm can substantially improve its economic and environmental performance by interacting, adopting and applying integrated, data-driven analytics and new technology. This paper presents a tool which was designed with a view to comparing the reproduction efficiency between farms with and without individual cow sensors (MooMonitor+, Dairymaster, Kerry, Ireland). The MooMonitor+ system accurately identifies when the animal is in heat. The tool was developed using *dynamic programming* in R (Shiny) and shows the changes of costs, revenues and net-return. The tool includes five panels (Reproductive Performance Indicators, Fertility General Report, Level of Milk Production, Summary and Economic Impact, Comparison with Farms using MooMonitor+). The model calculates from the first *Day In Milk* and stops when the last calf is born after successful insemination of each cow. The tool was tested using real data from farms. Differences in pregnancy rate of 20% (Farm 1) and 7% (Farm 2) (without MooMonitor+) and average pregnancy rate 27% (current average of farms with MooMonitor+) were recorded. The tool showed that this translated to farm profits of +124 (Farm 1) and +276 (Farm 2) EUR/Cow/Year, respectively. This improvement is partly caused by factors such as decreased breeding cost, decreased risk of culling and replacement costs, and increased milk production per cow.

Keywords: cost, fertility, individual cow sensor, profit

Introduction

The economic gains of improving reproductive performance arise from higher milk productivity leading to increased milk sales and potentially higher milk income over feed cost, greater calf sales, lower replacement and mortality costs and lower relative reproductive costs. These factors seem to be the most important determinants of economic reproductive efficiency (Giordano *et al.,* 2012; Galvao *et al.,* 2013). Highly productive farms tend to have good fertility; farms with poor fertility tend to be less productive and at the herd level, the high productivity is no excuse for poor fertility (Meadows *et al.,* 2005). The main economic impact of an increased calving interval on milk production is due to two effects. Firstly, increased calving interval means that the average production per cow per day will reduce as cows spend proportionally more time in late lactation where yields are lower and, secondly, during late lactation the margin between milk income and feed costs is lower and thus the profit margin per litre is less (Krpalkova *et al.,* 2014). Whatever system a farm uses, whether it is a seasonal spring-calving farm or a completely non-seasonal permanently housed farm, poorer fertility means that cows take longer to get pregnant. They are, therefore, at an increased risk of not being pregnant at the end of the breeding season (for the seasonal herd) or when they've been calved too long (in the non-seasonal system) (De Vries, 2004). The relationship between milk production and feed consumption is complex and interacts with many factors such as the herd structure, feed

price and the shape and persistence of lactation curves (Cabrera, 2012). Cabrera (2012) and Galvao *et al.* (2013) reported a combined synergistic and antagonistic effect of reproductive performance and milk income over feed cost at varying levels of 21-d Pregnancy Rate (PR). The gain in income over feed cost (US$) varied between +$9 (Giordano *et al.,* 2012) and –$2.4 (Galvao *et al.,* 2013) per 1% increase in 21-d PR. The number of days open may be one of the best indicators of current reproductive efficiency. Days open can be influenced by factors such as length of voluntary waiting period, heat detection accuracy, semen quality and breeding technique, nutrition, cow fertility, disease, or weather (Krpalkova *et al.,* 2016). The number of services per conception is directly related to the conception rate in a herd. Conception rate influences days open because if a cow does not conceive, she will be open for an additional estrous cycle (21 days) (Valergakis *et al.,* 2007). The cost of dairy AI straws is fairly consistent between AI companies, ranging between €15 and €25 depending on the bull used (Valergakis *et al.,* 2007). It means that cows with an additional five services per conception with an approximate cost of AI straw of €20 per cow will cost €100 more (Valergakis *et al.,* 2007). However, the cows are not serviced at each estrus cycle of extended days open, due to poor heat detection, but the loss is possible to calculate based on cost per extra day open (Kalantari and Cabrera, 2015). An economic value of US$ 3.2 to US$ 5.1 per cow per day was calculated in US dairy farms, when average days open increased from 112–166, heifer replacement being the main determinant of the total value (De Vries, 2006). Services per conception and days open will continue to rise, if problem cows are not culled (Krpalkova *et al.,* 2014). Conception rate problems may be caused by heat detection accuracy, length of voluntary waiting period, semen handling, semen quality, time of insemination, insemination techniques, reproductive tract infection, nutritional status, fertility, or weather (Krpalkova *et al.,* 2016).

Dairy farm profitability depends on a herd's reproductive performance, but this relationship is complex. Farmers and consultants can easily assess reproductive performance by benchmarking pregnancy rate (i.e. 21 d pregnancy rate) or other reproductive metrics, but they find it difficult to measure the economic impact (e.g. profitability) of changes in reproductive outcomes (Cabrera, 2012). This paper presents a tool that was designed with a view to comparing the reproduction level between farms with and without individual cow sensors (MooMonitor+, Dairymaster, Kerry, Ireland). The MooMonitor+ system accurately identifies when the animal is in heat. Precise identification of heat and good timing of artificial insemination resulted in improved heat detection rate, conception rate, pregnancy rate and finally, percentage of culled cows due to low fertility. The tool introduces the new technology (MooMonitor+ system) and calculates the differences in reproductive management within the same period regarding the economics of reproductive management.

Materials and methods

Individual cow sensor (MooMonitor+)

MooMonitor+ system improves farm profitability by decreasing labour requirements for farm personnel, improving reproductive performance and minimising losses due to missed heats. The cows wear a neck collar with the attached individual sensor (MooMonitor+). Current average pregnancy rate of farms using Moomonitor+ is 27% (Table 1).

Farms and data

The dataset consisted of two farms without MooMonitor+ system. Basic parameters were calculated based on the date of events in the created tools and are provided in Table 2. The initial structure of data in farms without MooMonitor+ includes date of events such as calving, heat, bred, pregnancy check, pregnancy, sign do-not-breed, cows in bullpen,

died and sold cows and abortion of cows. The dataset did not include milk yield and economic values. Only last or previous calving with the most subsequent information of cow was selected. Cows were removed from calculation if they remained open for all evaluated period and their DIM was lower than 250. Evaluated economic impact of current management in the farm and subsequent possible improvement due to accurately identified heat and good timing of artificial insemination with the system MooMonitor+ were calculated based on variables shown in Table 1. All the averages (Table 1) come from Eurostat (https://ec.europa.eu/eurostat), Teagasc (https://www.teagasc.ie/), MilkBot Model (Ehrlich 2011) or monitoring of Dairymaster customer farms and were used as a baseline for a final economic evaluation and can be changed according to conditions and records of evaluated farms and current averages of farm without MooMonitor+. These data were used for calculation of economic output (i.e. Income Over Feed Cost (IOFC), Cull cost, Reproductive Cost, Replacement Cost, Total Calves, Net Return) with current and subsequent improved management (MooMonitor+ system, pregnancy rate 27%).

Table 1. Average input variables of the model

Variables name	Average value
MilkBot[1] model (lactation curve)	
Average milk yield (kg/cow/d) [1]	33
Average milk yield 305 d (kg/cow) [1]	10 311
Peak milk (kg) [1]	39
Peak day (d) [1]	67
Improved reproductive management with MooMonitor+, PR (%)[2]	27
Voluntary waiting period (d) [2]	42
Body weight of lactating cows (kg/cow) [2]	560
Milk fat content (%)[2]	4
Feed price (EUR/kg feed) for lactating cows [2]	0.23
Feed price (EUR/kg feed) for dry cows [2]	0.20
Milk price (EUR/kg milk) [2]	0.35
Heifer replacement value (EUR/heifer) [2]	1,000
Average reproduction cost (EUR/cow/mo) <20% PR [2]	27
Average reproduction cost (EUR/cow/mo) >20% PR [2]	45
Cull cow value (EUR/cow) [2]	600
Calf value (EUR/Calf) [2]	200

[1] The MilkBot function (Ehrlich, 2011) was used to fit milk production curves.; [2] Source: Eurostat, Teagasc or monitoring of Dairymaster's farms.; PR=pregnancy rate

The degree of improvement in pregnancy rates and the time it takes to realise these improvements when using the MooMonitor+ depends on several different factors. The overall condition of the farm, as well as components such as culling policy, labour, age at first calving, body condition score, calving difficulties, management of negative energy balance, overall health status of cows and heifers, management of infertile and non-

cycling cows, environmental conditions, facilities, and so on, can all have an impact. The MooMonitor+ system can improve pregnancy rates within one year if the problem is the identification of heats and the timing of artificial insemination.

Model and parameters

The model, developed in R (Shiny package), was designed with a view to compare reproduction levels between farms with and without the MooMonitor+, and to show the changes of Costs, Revenues and Net Return. The tool was developed using *dynamic programming and* includes five panels listed below.

1. Reproductive Performance Indicators

Important reproductive performance indicators were graphically expressed (i.e. distribution of heat interval, DIM at first breeding, times bred, breeding interval (Equation 1), distribution of pregnant cows (%) from eligible cows to be bred according DIM and percent of cows meet the target (optimal) in days open and DIM at first breeding (Table 2 and Figure 1).

$$BI = (DOPN - DIM1B) / (1 - TB) \quad (1)$$

where *BI* = breeding interval; *DOPN* = days open; *DIM1B* = DIM at first breeding; *TB* = times bred.

Table 2. Average of reproductive indicators

Indicators	Farm 1		Farm 2	
	Mean	Median	Mean	Median
Heat interval (days)	102.1	79.5	85.6	67.6
Breeding interval (days) [1]	76.2	0	21.3	0
DIM at first breeding (days)	102.4	78	147.3	132
Times bred (n)	1.1	1	1.1	1
Days open (days) [2]	104.4	82	125.5	107.0
Heat detection rate (%)	29.7	30.8	18.7	18.4
Service rate (%)	29.7	30.8	14.1	12.8
Conception rate (%)	65.5	83	51.3	72.0
Pregnancy rate (%)	19.7	24	7	9
Number of cows (n)	1,186		3,623	

[1]Mean of Breeding Interval (days) was calculated only with values > 0 (Equation 1); [2] Mean of Days open (days) was calculated only for pregnant cows

2. Fertility General Report

All the events, such as ageing, involuntary culling, abortion, getting pregnant, calving etc. were adjusted to 21 d cycles according to date. The resulting table includes two dates (from and to) and the sum of cows in each state of mentioned 21 d cycles and calculated percentage of selected rate: heat eligible cows, heat, heat detection rate, total insemination, service rate, pregnancy eligible cows, pregnancy, conception rate, pregnancy rate and abortion.

3. Level of Milk Production

The MilkBot function (Ehrlich 2011) was used to fit milk production curves. The MilkBot predicts milk yields (Y) as a function of time after parturition. Four parameters: a (scale), b (ramp), c (offset), and d (decay), control the shape of the lactation curves (Ehrlich 2011). Details of the MilkBot model can be found here: http://dairysight.com/milkbot/model.). Average values for the Holstein breed during all evaluated lactations were used as initial values.

$$Y(m) = a\left(1 - \frac{e^{\frac{c-m}{b}}}{2}\right)e^{-d\times m}, \qquad [2]$$

Equation 2 was used to describe milk production curves for an average of all lactations according to the breed. In the model, it is possible to change all the milk parameters according to the current milk yield level in the evaluated farm. Milk production was also adjusted to decrease by a fixed factor of 5, 10 and 15% by month of pregnancy 5, 6, and 7, respectively, based on the methodology of De Vries (2004). Daily milk production was then calculated by summing up average milk production from Equation 2 and possible pregnancy milk depression based on fixed factors, always with the consideration of the milk class.

4. Summary and Economic Impact

The model used the average reproductive cycle of dairy cows of 21 d as the length of stage to better evaluation of reproductive management. Therefore, all the events, such as ageing, involuntary culling, abortion, getting pregnant, calving, starting a new lactation, milk production etc. were adjusted to 21 d cycles. Cows were ordered in 21 d cycles according to days in milk and days in pregnancy. The calculation started by placing a group of cows from first DIM and continued by moving it forward through all the defined states until the last calf was born in the first reproduction period.

The model calculated costs and revenues in two steps in order to compare current and improved management with MooMonitor+ system. Step 1 - all open cows after first calving moved through all 21 d stage from their first DIM (based on real data), Step 2 - all open cows after second calving moved through all 21 d stage from their first DIM (simulation of relevant management). Only calved cows from the first step were included in the calculation. The net return (€/cow/day) was calculated as follows:

$$\mathrm{NR} = \sum_{d=1}^{n}\sum_{p=0}^{13}\mathrm{IOFC}_{d,p} + CV_{d,p} - CC_{d,p} - RC_{d,p}, \qquad [3]$$

where d = DIM with 21 d steps; n = number of 21 d steps (differ based on evaluated farm); p = pregnancy and, NR is the net return; IOFC is milk income over feed cost; CV is income from calves, CC is the culling cost, which is the difference between the salvage value of the culled cow and the replacement heifer price, and RC is the average reproductive cost based on relevant management (Table 1). Results from this panel are shown in Table 2 and Table 3.

5. Comparison with Farms using MooMonitor+

Pregnancy rate was changed in the MooMonitor+ system in both previous steps according to the average value in Table 1. Improvement in involuntary culling, due to new technology MooMonitor+, was not included in the calculation. However, all cows with sign do-not-breed were not removed from the herd and were calculated as open (cows bred eligible) in the calculation of MooMonitor+ system. The voluntary waiting period was assumed to be 42 d to follow the 21 d stage length of the model. Cows were eligible for insemination from 42 d in the system of Moomonitor+ system to the day when the last calf was born in the

simulation process. According to a study by Kalantari and Cabrera (2015), it was assumed that herds with poor reproductive performance have invested less on management and facilities, which resulted in poor detection of estrus and/or worse overall conception rates. Thus, based on the estimated average 21 d PR, different reproductive cost (€/21-day) were assigned to each herd. Reproductive cost for farms with < 20% 21 d PR used €0.90/d and farms with > 20% 21-d PR used €1.50/d. However, both reproductive costs €0.90/d and €1.50/d and subsequent results are shown below in Table 3.

Results and discussion

Several authors have developed methodologies to estimate the financial cost of delayed pregnancy in dairy systems, based on computer simulation models (Groenendaal *et al.,* 2004; Meadows *et al.,* 2005; De Vries, 2006; Kalantari and Cabrera, 2015). Although the use of those models made it possible to achieve quite realistic results, the real data from farms was not used in these studies, which could make it difficult to comprehend by users. Thus, the methodology presented in this study was focused on developing a simpler tool to calculate the economic values based on real data. It is possible to change the average input variables in the tool listed in Table 1, making it useful to analyse different scenarios on the farm. The calculation showed the differences in reproductive management within the same period of the same cows, i.e. without data of new replacement due to culling. A decrease in the number of days between calving and conception (increased pregnancy rate), also known as days open, is typically associated with increased profitability in dairy cows (De Vries, 2006).

Table 3. Final reproductive economic analysis (EUR/Cow/Year)

Comparison	Farm 1					Farm 2				
	IOFC	RC	CC	CV	NR	IOFC	RC	CC	CV	NR
Current management	2,716	91	108	79	2,596	2,520	143	161	56	2,271
MooMonitor+ System	2,815	86 / 144[1]	102	93	2,720 / 2,662[1]	2,666	83 / 139	122	86	2,547 / 2,491[1]
Difference	*+99*	*+5/53*[1]	*-6*	*+14*	*+124 / 66*[1]	*+146*	*-60/4*[1]	*-39*	*+30*	*+276 / 220*[1]

[1] Different average reproductive costs were used according to different levels of pregnancy rate (< 20%, €0.90/day / > 20%, €1.50/day). (Equation 1).; NR is the net return; IOFC is milk income over feed cost; CV is income from calves, CC is the culling cost, which is the difference between the salvage value of the culled cow and the replacement heifer price, and RC is the average reproductive cost based on relevant management

Our study showed similar results where the net return increased by €124 or €66 (Farm 1) and €276 or €220 (Farm 2) per cow and year depending on the average of reproductive cost per day used (€0.90/day or €1.50/day, respectively; Table 3). However, the improvements were in both cases due to better pregnancy rate and also more cows were bred eligible in MooMonitor+ system (cows with sign do-not-breed were included in MooMonitor+ system calculation). In the example shown in this paper (Table 3), the culling costs were higher than reproductive cost in both farms with current management. According to Cataneo *et al.* (2015), infertility culling costs are the main cause of the involuntary days open after 120 days, whereas milk yield losses became the main determinant from 180 days. De Vries (2006) reported that cow replacement cost due to infertility represented the highest proportion of the total cost. Simulation of calculation according to average values of pregnancy rate of MooMonitor+ system decreased the culling cost and reproductive cost and increased milk income over feed cost and income from calves in both evaluated farms (Table 3).

For example, Giordano *et al.* (2012) aimed for very detailed construction of the reproductive programs including all the specifics related to reproductive costs evaluation (such as the cost of labour for estrus detection and injection, hormones for synchronization and pregnancy diagnosis) and daily reproductive dynamics of the herd. Kalantari and Cabrera (2015) included reproductive costs as a random parameter into the model and the assumption was that the herd with good reproductive performance has invested more. In the current study, reproductive costs were calculated as the sum of the average cost per day open with the same assumption. Reproductive costs at 15% 21-d PR level were approximated $40 per cow/year (Giordano *et al.*, 2012), $114 per cow/year (Giordano *et al.*, 2012) and in current study with 20% 21 d pregnancy rate (Farm 1, Table 1) €91 per cow/year. Income over feed cost increased in both farms with MooMonitor+ by €99 (Farm 1) and €146 (Farm 2) per cow per year. However, some studies showed that milk sales could decrease with increasing 21 d PR from 10–30% ($4,285 vs 4,184 per cow and year; Galvao *et al.*, 2013). This could be explained to a large extent due to a lower proportion of lactating cows when higher 21 d PR, which results in lower milk production. Other factors can be the shape and level of milk lactation curves Kalantari and Cabrera (2015). Our study showed that productivity of an individual cow might increase in better reproductive performance, but the way it interacts with herd structure (percentage of dry cows and lactating cows) and thereby, influencing the overall herd's milk production was not evaluated in our study. The distribution of remaining open cows in management without MooMonitor+ according to DIM for Farm 1 is shown in Figure 1 (44% open cows by 100 DIM and 31% open cows by 150 DIM). The distribution of remaining open in management without MooMonitor+ cows according to DIM for Farm 2 is shown in Figure 2 (72% open cows by 100 DIM and 63% open cows by 150 DIM).

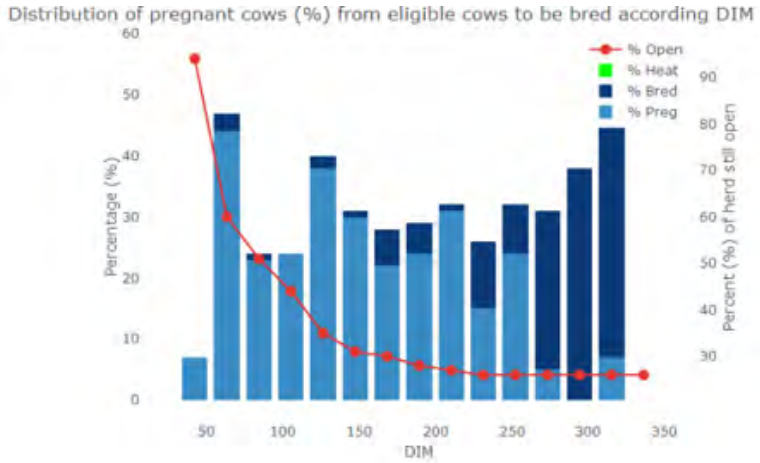

Figure 1. Reproductive analysis based on DIM from 1st panel (Farm 1, current management)

DIM = days in milk, Open = remained open cows; Heat = % of cows seen in heat and not bred, Bred = % of bred cows and not pregnant, Preg = % of pregnant cows

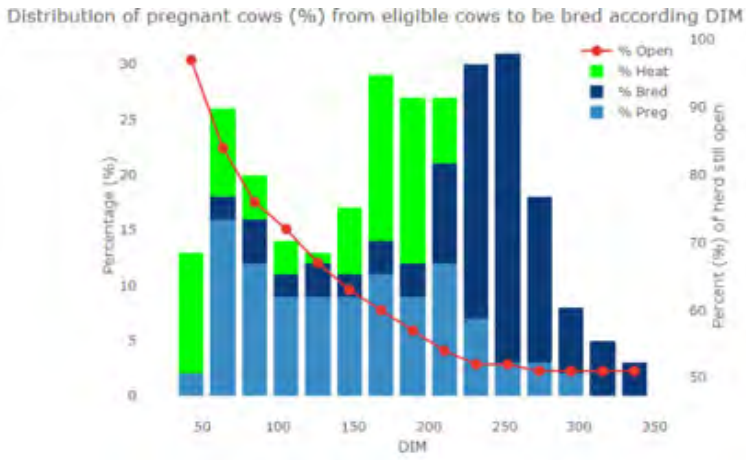

Figure 2. Reproductive analysis based on DIM 1st panel (Farm 2, current management)

DIM = days in milk, Open = remained open cows; Heat = % of cows seen in heat and not bred, Bred = % of bred cows and not pregnant, Preg = % of pregnant cows

Conclusion

The proposed methodology has demonstrated to be a simple tool for monitoring the financial impact of different reproductive scenarios in a dairy herd. Our study revealed the economic impact of better reproductive performance on an individual cow level. Poor fertility means that cows spend longer producing lower amounts of less efficiently produced milk with increased culling risk and this will negatively affect the net return of those cows. The tool then introduces the new technology (MooMonitor+ system) and current averages of pregnancy rate of 27% and subsequent economic impact of accurately identified heat and good timing of artificial insemination.

Acknowledgements

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References

Cabrera, V.E. (2012). A simple formulation and solution to the replacement problem: A practical tool to assess the economic cow value, the value of new pregnancy, and the cost of pregnancy loss. *Journal of Dairy Science*, 95: 4683–4698.

Cattaneo, A.L., Baudracco, J., Lazzariny, B., and Ortega, H. (2015). Methodology to estimate the cost of delayed pregnancy for dairy cows. Short Communication. Revista Brasileira de Zootecnia, 44: 226–229.

De Vries, A. (2004). Economics of delayed replacement when cow performance is seasonal. *Journal of Dairy Science*, 87: 2947–2958.

De Vries, A (2006). Economic value of pregnancy in dairy cattle. *Journal of Dairy Science*, 89: 3876–3885.

Galvao, K.N., Federico, P., De Vries, A and Schuenemann, G.M. (2013). Economic comparison of reproductive programs for dairy herds using estrus detection, timed artificial insemination, or a combination. *Journal of Dairy Science*, 96: 2681–2693.

Giordano, J.O., Kalantari, A. S, Fricke, P.M., Wiltbank, M.C. and Cabrera, V.E. (2012). A daily herd Markov-Chain model to study the reproductive and economic impact of reproductive programs combining timed artificial insemination and estrus detection. *Journal of Dairy Science*, 95: 5442–5460.

Groenendaal, H., Galligan, D.T. and Mulder, H.A. (2004). An economic spreadsheet model to determine optimal breeding and replacement decisions for dairy cattle. *Journal of Dairy Science,* 87: 2146–2157.

Kalantari, A.S., Cabrera, V.E. (2015). Stochastic economic evaluation of dairy farm reproductive performance. *Canadian Journal of Animal Science,* 95: 59 – 70.

Ehrlich, J.L. (2011). Quantifying shape of lactation curves, and benchmark curves for common dairy breeds and parities. *The Bovine Practicioner,* 45: 88–96.

Krpalkova, L., Cabrera, V.E., Kvapilik, J., Burdych, J. and Crump, P. (2014). Associations between age at first calving, rearing average daily weight gain, herd milk yield and dairy herd production, reproduction, and profitability. *Journal of Dairy Science,* 97: 1–10.

Meadows, C., Rajala-Schultz, P.J. and Frazer, G.S. (2005). A spreadsheet-based model demonstrating the non uniform economic effects of varying reproductive performance in Ohio dairy herds. *Journal of Dairy Science,* 88: 1244–1254.

Valergakis, G. E, Arsenos, G. and Banos, G. (2007). Comparison of artificial insemination and natural service cost effectiveness in dairy cattle Department of Animal Production. *Animal*, 1: 293–300.

Evaluation of the sensor system SMARTBOW for detecting estrus in confined dairy cows

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Abstract

Good reproductive performance is based on a reliable estrus detection and determination of the optimum insemination time. Nowadays, estrus detection is often challenging for farmers because of a decreased duration of the visual signs of estrus, a less expressive estrus behaviour and a high proportion of estruses occurring during night hours. Hence, various technical devices were developed to assist the farmers in estrus detection.

The company Smartbow GmbH (Weibern, Austria) developed the sensor system SMARTBOW for a wireless, continuous and real-time monitoring of dairy cows. The electronic ear tag contains an accelerometer for detecting head and ear movements in x-, y- and z-axis. Machine learning algorithms process the incoming data, analyse it for the expression of specific behaviours and activity levels and use the information for a purpose built decision function. Actually, data are available on an animal's activity, rumination and localisation inside a barn. The estrus detection function is primarily based on increased activity combined with distinct behavioural changes. Thresholds were developed by the company and the accuracy of the system for estrus detection was internally evaluated, so far.

In this independent study, the SMARTBOW system was installed in a large commercial dairy farm in Slovakia, housing approx. 2,700 Holstein Friesian cows. Retrospectively, 579 estrus events were used to evaluate the accuracy of estrus alerts generated by the system. Sensitivity, specificity, positive and negative predictive values, accuracy, and error rate for detecting estruses were 97%, 98%, 96%, 94%, 96%, and 2%, respectively.

In summary, the SMARTBOW system is suitable for reliable estrus detection in confined dairy cows.

Keywords: cow, reproduction, estrus detection, accelerometer

Introduction

Detecting cows in estrus as well as getting cows pregnant are two major challenges in herd management of dairy cows (Denis-Robichaud *et al.*, 2018). With increasing herd sizes, the available time per animal is continuously decreasing (Barkema *et al.*, 2015). Furthermore, the percentage of animals expressing standing estrus has declined to 50%, with an average duration of approximately 5 h (Dobson *et al.*, 2008). To achieve satisfactory estrus detection rates it is recommended to observe animals several times per day (Saint-Dizier & Chastant-Maillard, 2018). This, however, is quite time-consuming and requires the skills and knowledge of farmers and their employees of behavioural signs of cows in estrus, which are often not self-evident to paid farm workers.

Nowadays, several tools for estrus detection are available (Rutten *et al.*, 2013). The company Smartbow GmbH (Weibern, Austria) developed an ear-attached activity monitoring system. The SMARTBOW ear tag contains a 3D-accelerometer which collects data from cow head and ear movements that are processed and used for continuous automated

real-time monitoring. This technology has been evaluated and is commercially available for estrus detection, rumination monitoring (Borchers *et al.*, 2016; Reiter *et al.*, 2018) and localisation (Wolfger *et al.*, 2017).

The aim of this study was to evaluate the ear tag based 3D-accelerometer system SMARTBOW to detect cows in estrus. For this, reproductive performance data were retrospectively compared with estrus alerts generated by the sensor system.

Material and methods

All study procedures were approved by the institutional ethics committee of the University of Veterinary Medicine Vienna, Austria, in accordance with the national authority according to § 26 of the Law for Animal Experiments, Tierversuchsgesetz 2012 – TVG 2012 (BMWFW-68.205/0004-WF/V/3b/2016), as well as by the Slovakian Regional Veterinary Food Administration.

Herd description

The study was conducted on a Slovakian dairy farm, housing approximately 2,700 Holstein-Friesian cows. The average energy corrected milk yield (based on 4.0% butterfat and 3.4% protein) was 9,260 kg per cow and year. Cows were kept in freestall barns with pens for approximately 250 animals each, equipped with full concrete floors and high bed cubicles. All animal related events (e.g. estrus, artificial inseminations, clinical diseases, treatments) were entered into the herd management software DairyComp 305 (DC305, Valley Agricultural Software, Tulare, USA) by responsible farm personnel. Heifers were kept on another farm site, thus, only multiparous cows were included in this study.

Reproductive management

Reproductive management procedures were defined in the farm specific standard operating procedures (SOP) and not changed for this study. The voluntary waiting period was set at 50 days in milk (DIM). Estrus detection was performed with an automated monitoring device (CowManager Sensoor, Agis, Harmelen, Netherlands) and by visual observation by farm personnel during preparation for milking or by AI technicians in the pens. Artificial insemination (AI) was carried out by two AI technicians based on the am-pm rule (Trimberger, 1948). Cows not detected in estrus and not bred by 64 DIM were subjected to a standard Ovsynch protocol (Pursley *et al.*, 1995). A Resynch protocol was initiated 1 week before pregnancy check and was continued for non-pregnant cows. Pregnancy diagnosis was performed between 39–45 days after AI by the herd veterinarian by ultrasound and confirmed approximately 90 days after AI by transrectal palpation of the uterus and its contents by an AI technician. Animals excluded from inseminations were classified as 'do not breed' as they were generally excluded from the breeding program for various reasons or they did not get pregnant within 200 DIM.

SMARTBOW system

For study purposes, two pens of the farm were equipped with indoor receivers (SMARTBOW WallPoint). The ear tag was attached to the study animals in the middle of the right ear. Acceleration data (range -2 g to +2 g) of head and/or ear movements of the animals were recorded with a frequency of 1 Hz and sent in real-time to the receivers. Receivers were connected with a local server (SMARTBOW FarmServer), on which data were processed and analysed. When specific parameters (calculated on activity) and behaviour changes exceeded a defined threshold, an estrus alert was generated.

Study design and definition of terms

Inseminations resulting from an Ovsynch protocol were excluded from statistical analyses. The comparison between induced and natural estruses was not the intention of this study.

An estrus followed by AI that resulted in pregnancy was defined as 'golden standard' (GS). In our data set of GS events, abortions after diagnosed and confirmed pregnancies remained in the data set. In addition to GS events, which represent the highest reference level, we defined estrus events with an estrus interval of 18–25 d as 'true estrus' (TE) events, independent of whether estrus was followed by AI or pregnancy (Figure 1). This interval is close to the described range for duration of estrus (Forde *et al.*, 2011) and accounts for findings that the physiological estrus interval increases with parity and milk yield (Remnant *et al.*, 2015).

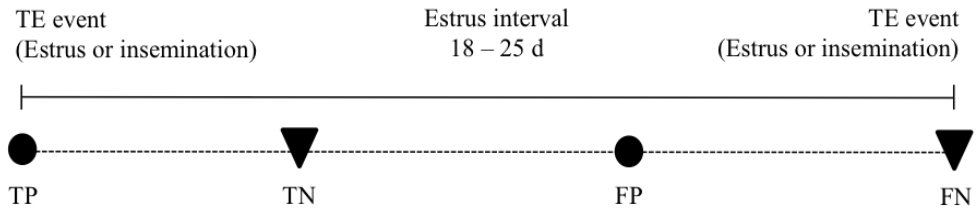

Figure 1. Example for assigning generated estrus alerts (●) or not generated alerts (▼) of the SMARTBOW system

For the evaluation of the performance of the SMARTBOW system, GS and TE events were determined retrospectively, based on reproductive performance data (i.e. estrus, insemination) entered into DC305 and matched with generated estrus alerts by the SMARTBOW system. If an estrus alert coincided with a GS or TE event, the alert was classified as 'true positive' (TP). Multiple alerts, which end and start times, respectively occurred within 36 hours were considered as single alert. More than 85% of multiple alerts occurred in a timeframe of one to four hours and more than 90% within one to nine hours. In the case that no estrus alert was generated during a GS or TE event, it was classified as 'false negative' (FN). An estrus interval was classified as 'true negative' (TN), when no estrus alert occurred, and as 'false positive' (FP), when an estrus alert occurred during an estrus interval (Figure 1).

Statistical analyses

To evaluate the performance of the SMARTBOW system for estrus detection, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), accuracy, and error rate (ER) were calculated with Microsoft Excel (MS Excel, version 14.0, Microsoft Corporation, Redmond, USA). Details are presented in Table 1.

Table 1. Parameters used for evaluating the performance of the SMARTBOW system

Parameter[1]	Calculation[2]	Definition[3]
Sensitivity	TP / (TP + FN) x 100	Proportion of identified GS / TE events among all GS / TE events
Specificity	TN / (TN + FP) x 100	Proportion of non-alerted estrus intervals among all estrus intervals
PPV	TP / (TP + FP) x 100	Proportion of detected TE events among all generated alerts
NPV	TN / (TN + FN) x 100	Proportion of non-alerted non-estrus events among all non-alerted events
Accuracy	TP + TN / (TP + TN + FP + FN) x 100	Proportion of identified events among all events
ER	FP / (FP + TP) x 100	Proportion of false estrus alerts among all generated alerts

[1]PPV = positive predictive value; NPV = negative predictive value; ER = error rate; [2]TP = true positive; FN = false negative; TN = true negative; FP = false positive; [3]GS = golden standard; TE = true estrus

For further statistics, the software package SPSS (version 24, IBM Corporation, Armonk, NY) was used. The level of significance was defined as $P < 0.05$ for all statistical tests.

Results

Cows or events were excluded if study animals left the study area too early or because of inseminations induced by an Ovsynch protocol. For the evaluation of the estrus detection performance of the SMARTBOW system, a total of 316 GS events in 316 cows and 263 TE events divided by 142 estrus intervals in 116 cows were used. It was possible that more than two TE events occurred per cow and that two subsequent TE events were followed by another TE event after 18–25 days. Estrus was detected in 306 of 316 GS events with the SMARTBOW system, resulting in a sensitivity of 96.8%. Additional results for TE are presented in Table 2.

Table 2. Test characteristics of the SMARTBOW (SB) system for detecting estrus events

Events[1]	Cows	SB results	True (+)	False (-)	Statistics[2]%			
					Se	Sp	PPV	NPV
GS	316	Alert (+)	306[a]	n.a.[3]	96.8	n.a.	n.a.	n.a.
		No Alert (-)	10[a]	n.a.				
TE	116	Alert (+)	254	6	96.6	97.7	95.8	93.8
		No Alert (-)	9	136				

[1]GS=Golden standard events; TE =True estrus events [2]Se=Sensitivity; Sp=Specificity; PPV=Positive predictive value; NPV=Negative predictive value; [3]n.a.= Not available

Discussion

Precision dairy farming technologies have a tremendous potential to improve health, welfare, and reproduction in dairy cattle (Barkema *et al.*, 2015). An increase in average herd size, the limited availability of skilled workers, and pressure on efficient farm management are factors for developing automated farm monitoring systems. These factors are encouraging considerations for farmers to adopt automated estrus detection systems (Gargiulo *et al.*, 2018).

The objective of this study was to evaluate the suitability of a novel ear-attached accelerometer system for estrus detection in indoor housed dairy cows. As the highest level of reference, GS events in this study were confirmed by pregnancy and, hence wholly certifying that cows had been in estrus. The sensitivity for GS events was 97%. Compared to outcomes from other studies using progesterone measurements as the golden standard, sensitivity ranged from 63–71% for pedometers (Roelofs & van Erp-van der Kooij, 2015), from 76–80% for neck collar activity-meters (Roelofs *et al.*, 2017), and from 56–84% for collar-mounted accelerometers (Løvendahl & Chagunda, 2010). As an additional reference level that is independent from AI outcome, TE events were defined in our study. Results showed that sensitivity for detecting TE events with the SMARTBOW system was quite similar to the detection of GS events. This demonstrated that the SMARTBOW system is suitable for automated estrus detection in dairy cows.

The PPV in this study was calculated as 96% and was greater than in other studies where the PPV ranged from 71–74% for pedometer (Roelofs & van Erp-van der Kooij, 2015) and from 84–92% for neck collar activity-meters (Roelofs *et al.*, 2017). The specificity of the SMARTBOW system (98%) is comparable with the results for neck collars (99–100%) and leg activity-meters (100%) in indoor kept dairy cows (Roelofs *et al.*, 2017).

Conclusion

By recording an increase of activity as well as specific changes in animal behaviour, the sensitivity, specificity, PPV, NPV, accuracy, and ER of the SMARTBOW system for detecting estrus events were 97%, 98%, 96%, 94%, 96%, and 2%, respectively. Hence, the system is eligible for an automated detection of estrus events in indoor housed dairy cows. Further studies should investigate the effect of different conditions of housing (e.g. pasture-grazed, outdoor-pad), and floors and surfaces (e.g. slatted floor, rubber, sand) on the performance of estrus detection by the SMARTBOW system.

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References

Barkema, H.W., von Keyserlingk, M.A.G., Kastelic, J.P., Lam, T.J.G.M., Luby, C., Roy J-P., LeBlanc S.J., Keefe, G.P. and Kelton, D.F. (2015). Invited review: Changes in the dairy industry affecting dairy cattle health and welfare. *Journal of Dairy Science,* 98: 7426–7445.

Borchers, M.R., Chang, Y.M., Tsai, I.C., Wadsworth, B.A. and Bewley, J.M. (2016). A validation of technologies monitoring dairy cow feeding, ruminating, and lying behaviors. *Journal of Dairy Science,* 99: 7458–7466.

Denis-Robichaud, J., Cerri, R.L.A., Jones-Bitton, A. and LeBlanc S.J. (2018). Dairy producers' attitudes toward reproductive management and performance on Canadian dairy farms. *Journal of Dairy Science,* 101: 850–860.

Dobson, H., Walker, S.L., Morris, M.J., Routly, J.E. and Smith, R.F. (2008). Why is it getting more difficult to successfully artificially inseminate dairy cows? *Animal*, 2: 1104–1111.

Forde, N., Beltman, M.E., Lonergan, P., Diskin, M., Roche, J.F. and Crowe, M.A. (2011). Oestrous cycles in Bos taurus cattle. *Animal Reproduction Science,* 124: 163–169.

Gargiulo, J.I., Eastwood, C.R., Garcia, S.C. and Lyons, N.A. (2018). Dairy farmers with larger herd sizes adopt more precision dairy technologies. *Journal of Dairy Science*, 101: 5466–5473.

Løvendahl, P. and Chagunda, M.G.G. (2010). On the use of physical activity monitoring for estrus detection in dairy cows. *Journal of Dairy Science*, 93: 249–259.

Pursley, J.R., Mee, M.O. and Wiltbank, M.C. (1995). Synchronization of ovulation in dairy cows using PFG2α and GnRH. *Theriogenology,* 44: 915–923.

Reiter, S., Sattlecker, G., Lidauer, L., Kickinger, F., Öhlschuster, M., Auer, W., Schweinzer, V., Klein-Jöbstl, D., Drillich, M. and Iwersen, M. (2018). Evaluation of an ear-tag-based accelerometer for monitoring rumination in dairy cows. *Journal of Dairy Science,* 101: 3398–3411.

Remnant, J.G., Green, M.J., Huxley, J.N. and Hudson, C.D. (2015). Variation in the interservice intervals of dairy cows in the United Kingdom. *Journal of Dairy Science,* 98: 889–897.

Roelofs, J.B., Krijnen, C. and van Erp-van der Kooij, E. (2017). The effect of housing condition on the performance of two types of activity meters to detect estrus in dairy cows. *Theriogenology,* 93: 12–15.

Roelofs, J.B. and van Erp-van der Kooij, E. (2015). Estrus detection tools and their applicability in cattle: recent and perspectival situation. *Animal Reproduction,* 12: 498–504.

Rutten, C.J., Velthuis, A.G.J., Steeneveld, W. and Hogeveen, H. (2013). Invited review: Sensors to support health management on dairy farms. *Journal of Dairy Science,* 96: 1928–1952.

Saint-Dizier, M. and Chastant-Maillard, S. (2018). Potential of connected devices to optimize cattle reproduction. *Theriogenology,* 112: 53–62.

Trimberger, G.W. (1943). Breeding efficiency in dairy cattle from artificial insemination at various intervals before and after ovulation. *Bulletin of the Agricultural Experiment Station of Nebraska,* 153: 3–25.

Wolfger, B., Jones, B.W., Orsel, K. and Bewley, J.M. (2017). Technical note: Evaluation of an ear-attached real-time location monitoring system. *Journal of Dairy Science* 100: 2219–2224.

Calving alert system – a helping technique or a welfare problem?

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Abstract

It can be a challenge for beef and dairy farmers to predict when a cow is close to calving, to move her to a calving pen in time and to properly monitor and assist the calving. The objective was to evaluate how a calving alert system, attached to the tail, affects the cow. The system monitors the tail's movements, and the farmer is notified via a text message to the mobile phone approximately one hour before calving. A case-control and an interview study were carried out. In the case-control study, cow behaviour was observed during and after the procedure of attaching the sensor on the tail. Controls were equally prepared, but the sensor was attached and then immediately removed again. The ethogram protocol contained behaviours like, for example, back arching, tail lifting, fidgeting and kicking. The case-control study had to be discontinued due to the sensors causing damage to the cow's tail and therefore, there were too few cows included in the study to be able to determine if there were statistical differences between the test and control cows. In the interview study which included 15 interviewed farmers, 80% stated that the cows' behavioural reaction was negative when the sensor was attached. Almost all farmers had observed damage to the tails after using the sensor and 20% had observed such severe damage that amputation was necessary.

Keywords: Animal welfare, behaviour, cow, monitoring

Introduction

In beef production, spring is a hectic period for many farmers, as calving is often concentrated to a limited period of time, with stress and too little sleep as common consequences. Farmers have also stated that the work around calving is one of the most risky and stressful work operations on the farm (Geng *et al.*, 2013). The increased workload with the pregnant cows can have negative consequences on the farmer's working environment, but also financial consequences and animal welfare problems if calves or cows die. Therefore, there is a need for technical aids that can facilitate the supervision of pregnant cows in both beef and milk production. A sensor that monitors the cow and alerts the farmer when it is time for calving is an aid that could complement the human supervision and the calving calendar, thereby contributing to decreasing stress levels and distress by the farmer during the calving period and a better utilised working time. Such a supplement may also reduce the risk of losing cow or calf as a result of complications during calving, as a more precise calving time allows the farmer to detect calving at an early stage and assist at the right moment when needed. There are various types of calving alert systems available on the market that have been tested and evaluated in previous studies, e.g. detectors that measure the cow's activity level, position and the rumination frequency, contractions of the uterus, tail lifts and detectors that measure temperature vaginally (Canger *et al.*, 2008; Clark *et al.*, 2015; Saint-Dizier & Chastant-Maillard, 2015; Ouellet *et al.*, 2016). It is important that these types of animal monitoring sensors are user-friendly, reliable and do not adversely affect the animal's health or well-being.

The company Moocall has developed a sensor that constantly monitors the activity of the cow with a sensor technique that measures the tail's movements. By measuring the movement pattern of the tail, indications of obstetric pain can be recorded, and the system sends a text message to a mobile phone on average one to two hours before calving.

The objective of this study was to evaluate how a calving alert system, attached to the tail, affects the cow's behaviour and welfare. Further, the objective was to investigate how farmers, who have used the product, experience how it functions and the pros and cons with using the calving alert system.

Materials and methods

Moocall is a commercially available sensor that is attached around the tail of the cow. The sensor costs approximately €300 and subscriptions for the first year are included. After the first year, an annual subscription cost is charged. The sensor is 15 cm long and weighs 250 g. The standard strap is 16 cm long, but there is a longer strap that fits larger breeds, and which can be ordered through the company if necessary. The sensor is provided with a rubber insert on the inside, and there is an extra rubber insert that can be used if the tail is slim. Since this study started, the company has developed a new rubber insert. The main difference is that the new insert is larger and has rubber gripping studs that are angled instead of standing straight. The sensor is placed on the cow's tail in front of the vulva, where it is attached around the tail with a specially designed locking system. The strap is tightened with a lever on the locking system, and according to the manufacturer's instructions, the strap should be tightened by moving the lever back and forth 1-2 times. Moocall calving sensor detects tail movements and when increased activity and higher tail lift are detected, the farmer is informed via SMS to one or two phone numbers. The sensor works for all breeds and works everywhere in the world where there is a GSM signal. No additional hardware is needed, but a subscription needs to be renewed annually. The sensor has a rechargeable battery that is charged with a USB cable that connects under a waterproof cover. The battery life is 30+ days and the device sends an SMS alert when there is 15% battery charge left.

A case-control study and an interview study with farmers were carried out. In the case-control study, cow behaviour was observed during and after the procedure of attaching the Moocall calving sensor with the older rubber insert on the tail. Controls were equally prepared, but the sensor was first attached and removed again within 30 seconds. The ethogram protocol contained behaviours like, for example, back arching, fidgeting, kicking and tail lifting. Direct observations of the cow's behaviour were conducted during two periods for the control cows and three periods for the test cows. The first observation period was when attaching the calving alert system on the tail, the second observation period began when the cow was released from the chute and the third observation period was approximately 60 minutes after the cow had been released from the chute. Each cow (including controls without a sensor and test cows with sensor attached) was observed for five minutes during the second observation period, when the cow was on pasture. Thus, it was only the test cows that were observed in the third observation period and the total observation time was 15 minutes per test cow and 10 minutes per control cow, in addition to the time when the sensor was attached to the tail.

An interview study with farmers was carried out with 15 of 21 farmers that either used the sensor frequently, only used the sensor occasionally or had stopped using the sensor. The interviews were semi-structured telephone interviews, which included eight questions about the calving period and 25 questions about the calving sensor. The interviews included topics such as why the farmer used the calving sensor, how the farmer experienced the work situation around calving and how the calving alert system facilitates the work of matching cow and calf as well as the pros and cons of the technology. The interviews were recorded and transcribed and then analysed by compiling the answers to each question in the interviews.

Results and discussion

The case-control study had to be discontinued due to the sensors causing tissue damage to one cow's tail. As the tail damage was noted within the first four test cows, there were too few cows included in the study to be able to determine if there were statistical differences in behaviour between the test and control cows. However, the practical experience from the case-control study indicated that it was difficult to know how hard the sensor should be fastened to the tail and there was no control function to ensure the strap was not tightened too hard. Of the four devices tested, one fell off after just three minutes and two fell off during the first day. The fourth sensor was taken off the day after attachment, and tissue damage and tourniquet marks were observed on the tail where the sensor had been attached. The time it took to attach the sensor to the tail was on average 1.3 minutes, but varied between 22 seconds up to 5.3 minutes. The reason for the longer attachment time for some cows was that they had very thick tails which made it difficult to fasten the locking system properly. Removing the sensor only took 3-8 seconds per animal.

Of the 21 Swedish farmers who had bought the calving alert system, 15 agreed to participate in the telephone interview. Three of the interviewed farmers used the sensor at the time of the interview, five used it but not routinely, and seven had stopped using the sensor. One farmer had used both the new and the older version of the rubber insert, otherwise the farmers had used the older model of the rubber insert. Six of the interviewees were women and nine were men. According to the interviewed farmers, the Moocall calving sensor functioned well technically and not many false alarms were experienced. In accordance with the manufacturer's manual, there were usually two alarms before calving began. All farmers found it easy to attach the sensor to the tail, but 93% had experienced that it was difficult to know how tight the sensor should be attached, and that there was a tiny distinction between the sensor being fastened too tight or too loose.

Several of the interviewed farmers pointed out that they did not let the sensor sit on as long as recommended in the Moocall manual due to the risk of tissue damage to the tail. If the calving sensor has to be taken off after just a few hours to allow the tail to rest and thereby avoid tail damage, both the usability and the possible time savings are reduced. It also indicates that the sensor may be best suited for dairy herds, since dairy cows are more used to being handled than cows in beef production. However, dystocia, i.e. calving complications, is more common in cows of beef breed than in dairy cows, which means that there may be greater benefit with a calving alert system in herds with beef production. Furthermore, in beef herds natural covering is most common, which entails additional challenges with the Moocall calving sensor, as it is more difficult to predict the expected calving date. Not knowing the exact date of fertilisation increases the risk of attaching the calving sensor too early prior to calving or not putting it on in time before the calving.

Results from the interview study showed that 80% of the interviewed farmers stated that the cows' behavioural reaction was negative when the sensor was attached to the tail and that the reaction lasted up to one hour after it was attached. The farmers had observed that the cows fidgeted or waved the tail more. Pain behaviour in cows can be very difficult to observe as cows have the ability to radiate calmness despite possible pain (Mee, 2008; Bech Gleerup *et al.*, 2015). Most of the farmers (87%) had observed damage to the tails after using the sensor, e.g. tourniquet marks (87%), swelling (53%), wounds (33%) or that the tail had died and was amputated (20%). According to the interviewed farmers, the tail injuries could last up to several months. Of the six farmers who declined to participate in the interview, four stated that they had stopped using the calving alert system because it gave tissue damage and tourniquet marks on the tails and one farmer stated that after reading

the instructions, he decided that the sensor would be too time consuming to use. The one farmer who had tested both the old and the new model of the rubber insert found that the newer model was easier to attach to the tail and did not fall off as often, but according to the farmer, the new rubber insert did not solve the problem of strangulation of the tail.

The results of this study showed that there were both advantages and disadvantages with the calving alert system. The main advantages, according to the interviewed farmers, were that it facilitated a better monitoring of the calving and thus, allowed the farmers to assist the calving in time when needed. The timing to initiate calving assistance is important, as there is a risk of doing more damage if the ligaments are not sufficiently stretched (Mee, 2008).

Conclusions

The main conclusion is that the calving alert system, in its current design, cannot be recommended as it may cause damage to the cows' tails. There is a need for functioning calving detectors both in dairy and beef production, which is why a further development of the existing Moocall calving sensor is encouraged. A better designed locking system with an added control function to ensure the correct tightness of the strap as well as user recommendations with the welfare of the cow in focus (e.g. decreased maximum time the sensor should be attached to the tail) are examples of needed improvements.

The studied calving alert system functioned well technically according to the interviewed farmers, but the risk of tail damage indicates that the cows may experience discomfort by the sensor and that using the sensor can be associated with welfare problems for the cows.

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References

Bech Gleerup, K., Haubro Andersen, P., Munksgaard, L. & Forkman, B. (2015). Pain evaluation in dairy cattle. *Applied Animal Behaviour Science*, 171: 25–32.

Cangar, Ö., Leroy, T., Guarino, M., Vranken, E., Fallon, R., Lenehan, J., Mee, J., Berckmans, D. (2008). Automatic real-time monitoring of locomotion and posture behaviour of pregnant cows prior to calving using online image analysis. *Computers and Electronics in Agriculture*, 64: 53–60.

Clark, C.E.F., Lyons, N.A., Millapan, L., Talukder, S., Cronin, G.M., Kerrisk, K.L. & Garcia, S.C. (2015). Rumination and activity levels as predictors of calving for dairy cows. *Animal,* 9(4): 691–695.

Geng, Q., Field, W.E., & Salomon, E. (2013). Risk assessment of working environment during cattle handling on pasture using WEST-AG. ISASH Technical Papers 13-TP2. *The Conference of International Society for Agricultural Safety and Health. June 23-27, 2013*, Sawmill Creek Resort - Sandusky, Ohio, USA.

Mee, J.F. (2008). Prevalence and risk factors for dystocia in dairy cattle: A review. *The Veterinary Journal*, 176: 93–101.

Ouellet, V., Vasseur E, Heuwieser, W., Burfeind O, Maldague, X. & Charbonneau, É. (2016). Evaluation of calving indicators measured by automated monitoring devices to predict the onset of calving in Holstein dairy cows. *Journal of Dairy Science*, 99: 1539–48.

Saint-Dizier, M. & Chastant-Maillard, S. (2015). Methods and on-farm devices to predict calving time in cattle. *The Veterinary Journal*, 205: 349–356.

Economics of using automatic lameness detection system for diagnosing different severity levels of lameness in dairy cows: A dynamic programming approach

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Abstract

Epidemiological data establish that lameness is second only to mastitis as dairy industry's most prevalent and costly animal welfare issue. Farmers using automatic lameness detection (ALD) system for continuous, accurate detection, coupled with proper treatment can reduce economic losses from lameness. It is reasonable to assume that the cost of lameness would vary with its severity. So our first objective was to estimate the cost of different lameness severity levels as a function of milk production, lameness risk, conception probability, mortality and treatment cost using a dynamic programming model. Our second objective was to conduct a cost benefit analysis for an ALD system which can reduce production losses through early detection of lameness, when compared to human-detection. The optimal profit per cow per year under assumed expenses and revenues reduced from $426.05 (when lameness incidence was assumed to be near 0%) to $388.12 when lameness incidence was assumed to be 19.7% (7.5% moderate and 12.2% severe cases). Cost per case was $192.54 at 19.7% lameness incidence. We used an operational framework which compared the lameness costs between human and ALD systems with 25%, 50% and 75% net avoided costs (NAC) for the 10 yr lifespan, at low, medium and high lameness prevalence scenarios. The break-even cost per cow per yr for using automatic LDS versus human LDS ranged from $13 (low incidence and 25% NAC) to as high as $99 (high incidence and 75% NAC) and justified the investment in automatic LDS with default price and 10 yr lifespan.

Keywords: Dairy cows, lameness severity, automatic lameness detection, economic modeling

Introduction

Lameness is a costly animal welfare and production problem burdening dairy producers worldwide (Green *et al.,* 2002; Booth *et al.,* 2004). Economic losses due to lameness depend on the cause of lameness (Bruijinis *et al.,* 2010; Cha *et al.*, 2010); average cost estimates range from $120 for a case of foot rot to $216 for sole ulcer. Major contributors to economic loss due to lameness include lost milk production (Enting *et al.,* 1997; Warnick *et al.,* 2001), reproduction problems (Hernandez *et al.,* 2001; Machado *et al.*, 2010), increased mortality and culling (Booth *et al.,* 2004; Machado *et al.,* 2010), and treatment costs (Cha *et al.*, 2010). To estimate the cost of a lameness case, parameters relating to these factors (i.e. milk loss, fertility decline, mortality and treatment cost) are needed. The cost of lameness would presumably vary with its severity (Hernandez *et al.,* 2005; Bicalho *et al.,* 2008). Not much research however, has been published on the economic consequences of lameness severity in dairy cattle (Bruijinis *et al.,* 2010) at the individual cow level. Hence, our first objective was to estimate the cost of different lameness severity levels at individual cow

level, as a function of milk production losses, lameness risk, pregnancy rate, mortality and treatment cost. Timeliness of detection, diagnostic accuracy, and efficacy of therapy are key factors limiting production losses associated with lameness (Hernandez *et al.,* 2005). The challenge is to accurately identify lameness at its onset to enable early therapeutic and preventive intervention. Effective reduction in prevalence can occur with the use of automatic lameness detection (**ALD**) systems that enable producers to accurately recognise lameness and then develop producer-driven programs of early and efficacious intervention (Whay *et al.,* 2002; Barker *et al.*, 2010). Farmers' adoption of such ALD systems mainly depends on their cost, sensitivity and specificity (Van De Gucht *et al.*, 2017, 2018). Hence our second objective was to estimate the cost of lameness at different ALD system efficiencies for various plausible prevalence rates of lameness. Additionally, the net avoided costs (NAC) by the ALD system (due to different efficiencies) were used to conduct a cost benefit analysis for ALD investment at different ALD system prices, system efficiencies, herd sizes and lameness prevalences.

Materials and methods

We adapted an existing dynamic optimisation and simulation model (**DP**; Cha *et al.*, 2010) in order to estimate the cost of lameness for cows with three different severities of lameness, namely for sound cows, moderately lame cows and severely lame cows. The model was further adapted to estimate the cost of lameness at different prevalences and different reductions in production losses due to the use of an ALD system with three different efficiencies.

Dynamic programming process

The DP model was constructed as a 3-level hierarchic Markov process using the multi-level hierarchic Markov process (MLHMP) application program interface (Kristensen, 2003). Hence a cow's life is described in numerical terms as three levels as shown in Figure 1. The three levels are namely: 1) At the founder (parent) level a cow can be in any of the five permanent (i.e. genetic potential) milk yield categories (kg): -5, -2.5, 0, +2.5, and +5 deviations (denoted by striped ovals ("a") at the left of the figure) from the mean level of milk production per day. The state variable at the founder level described the genetic potential of a cow and was permanent throughout the cow's life span. 2) The child level had eight different stages (child squares), each of which denotes one whole lactation. 3) The grandchild levels were divided into 20 (only seven grandchild squares are shown in Figure 1) stages of one month lactation length. As a cow moves from stage to stage, her state changes. We assume that decisions (replace, keep, treat or inseminate) are made at the end of each stage (month), and the effects of lameness occur in the following stage. The model gives the policy that maximizes the net present value (**NPV**) from a cow present in all combinations of stages and states mentioned above and their potential replacements (average-producing heifers), over a specified time period (one year, in the case of the current study). It involves choosing an arbitrary set of decision rules for each state at each stage, and solving a set of equations describing the expected future rewards over an infinite number of stages so that a decision which maximizes the NPV is reached in the last stage.

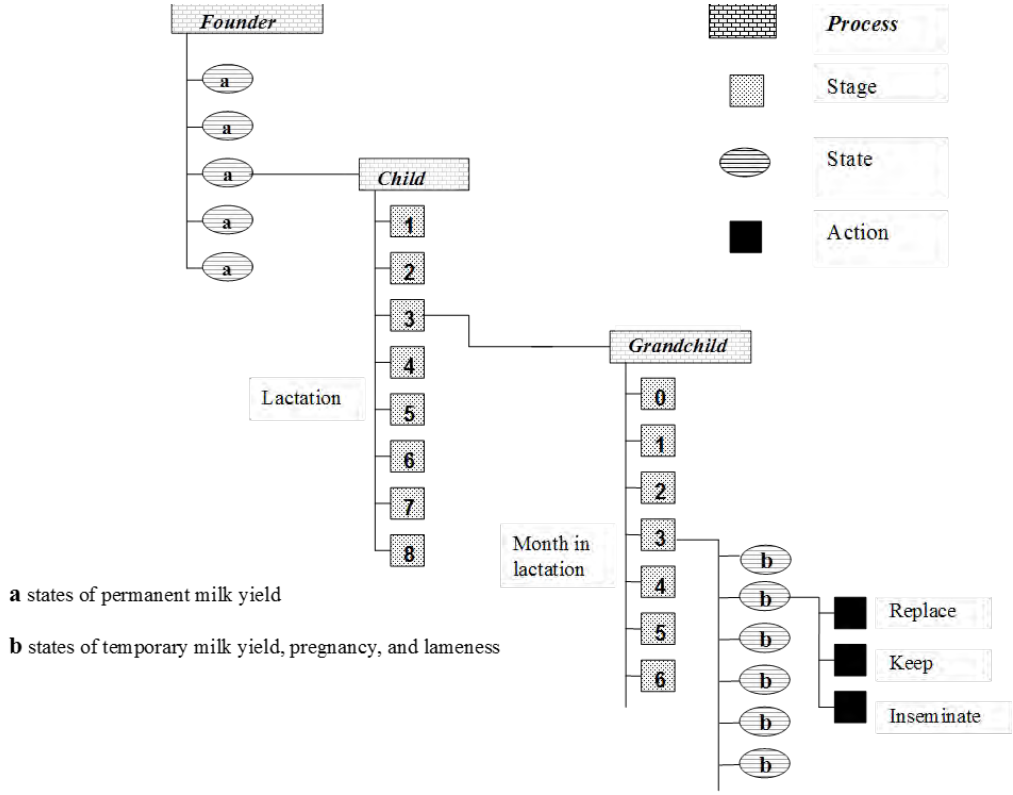

Figure 1. Schematic representation of the structure of the dynamic programming economic model used in this study to determine the costs and optimal management strategies for cows with different severities of lameness (Cha *et al.*, 2010)

Model parameters

A generalised linear mixed model (PROC MIXED in SAS, version 9.2; SAS Institute Inc., Cary, NC; Gröhn *et al.*, 2004) was used to estimate the effects of the lameness scores on milk yield in multiparous cows, based on the two year epidemiological data available from a Pennslyvania farm. All other input parameters (milk yield loss in primiparous cows, pregnancy rate, treatment cost, lameness incidence risk) were obtained from the literature. Economic and technical input parameters, many of which are beyond the farmer's control, were retained as in Cha *et al.* (2010). The average cost of lameness is the difference in the average net returns per cow per year for a herd with lameness, and the net returns per cow per year for a herd with no lameness. The average cost per case of lameness was calculated by dividing the cost of lameness by the percentage of lameness cases.

Cost benefit analysis for the automatic lameness detection systems

We used the conceptual framework described by Van De Gucht *et al.* (2018) to estimate the net avoided cost (**NAC**) of the ALD system, using the assumption that an ALD system with a given efficiency will detect lameness early and the corresponding early therapeutic intervention will reduce the lameness induced production losses. The default system (HD system) had the default production losses. The ALD systems with 25%, 50% and 75% efficiencies were assumed to have 75%, 50% and 25% of the default production losses due to early intervention. Cost benefit analysis for two different machine costs ($10,000, and

$50,000) were done. As the prevalence of lameness can vary highly among dairy herds, our analysis considered herds with three different prevalences. In the herd with low prevalence we assumed 25% subclinical and 20% clinical cases. The herd with medium prevalence had 75% subclinical and 43% clinical cases. The herd with high prevalence had 125% (more than 1 case per cow per year) subclinical and 65% clinical cases. As herd size is also a relevant variable which can affect the economic value of ALD systems, we calculated the year of breaking even for the ALD system investment (out of the 10 year system lifespan) under 12 different herd sizes (a herd size of 100 to a herd size of 1,200). As ALD system investment, ALD system efficiency, ALD system lifespan, lameness prevalence and herd size affect the economic decision to adopt the ALD system, our cost benefit analysis investigated the year of breaking even for an ALD system in 216 (two machine prices, three machine efficiencies, three lameness prevalences and 12 different herd sizes) scenarios.

Results and discussion

Lameness cost in default scenario

In the default scenario run, lameness incidence in the herd was assumed to be 0% (ideal situation). Here, the optimal profit (average across all cow characteristics) per year (i.e. the net return per cow per year) under assumed expenses and revenues (model inputs) was $426.05 (Table 1). We next ran a scenario approximating an "average" herd, in which the total lameness incidence was assumed to be 19.7% (comprised of 7.5% moderate cases and 12.2% severe cases). The profit (net return) per cow per year decreased from $426.05 to $388.12. Lameness was assumed to be detected using visual locomotion score in this scenario. The average cost per lameness case was $192.54 under this scenario (Table 1).

Cost of lameness for low, medium and high prevalence herds

As a general principle net returns per cow decreased as the prevalence rates increased. Hence net returns per cow per year were $344, $231, and $139.18 for scenarios with low, medium and high prevalences of lameness respectively (Table 1), under the case where HD systems (for default production losses assumed) were used for lameness detection. As a result of increased prevalence, the average cost of lameness was $82.05, $195.05, and $286.87 (Table 1) in low, medium and high prevalence scenarios respectively. As prevalence increased across the scenarios the optimal proportion of cows to be treated decreased from 94.34% (low prevalence) to 92.34% (high prevalence). As a rule of thumb when the efficiency of the ALD system improved, the net return per cow per year improved and as a result the average cost of lameness decreased. At 25% efficiency, the herd net returns were $357.30, $257.40, and $172.78 (Table 1) for low, medium and high prevalence scenarios, respectively. A similarly increasing pattern in net return could be seen in scenarios with 50% and 75% efficiency within each prevalence level.

Cost benefit analysis of automatic lameness detection machine

The break-even cost of an ALD system with 25% efficiency per cow was $13.3 ($82.05 - $68.75), $26.4 ($195.05 - $168.65) and $33.6 ($286.87 - $253.27) for the low, medium, and high prevalence scenarios, respectively, under the assumed production loss estimates our model used (Table 1). As the efficiency of the ALD system increases the maximum amount chargeable per cow will increase, as can be inferred from Table 1. As the benefit from investment in an ALD system is cumulative over the years (limited by system lifespan), we calculated the cumulative gain (NAC by the ALD system – cost due to lameness in HD system) for 18 scenarios (three prevalences, three ALD system efficiencies, two different herd sizes). A discount rate of 5% was considered for this investment analysis. In the 1,000 cow herd the investment in ALD broke even by year 5 for all nine scenarios, when the

cost of the ALD machine considered was $50,000 (with 10% annual maintenance cost). In the case of a 250 cow herd, the $50,000 investment in ALD did not break even in five out of nine scenarios (mostly the low (25%) efficiency scenarios). Figure 2 shows the year in which investment in ALD systems will break even for 216 scenarios (12 herd sizes, three machine efficiencies, two different ALD system prices, three different levels of lameness prevalence), out of which 194 scenarios broke even within the system lifespan of 10 years. Within the scenarios with the same ALD system price, the year of breaking even was early as the prevalence rate as well as the ALD system efficiency increased, for the same herd size. In the case of a 100 cow herd, a $10,000 ALD machine did not break even in low prevalence with a 25% efficiency, but broke even in years 6 and 4 for medium and high prevalence scenarios respectively. As the ALD system cost increased from $10,000 to $50,000 the herd sizes less than 800 did not break even in low prevalence, 25% efficiency scenarios (Figure 2). Hence, as a general rule of thumb, low ALD system price, at high herd size, high prevalence of lameness and high ALD system efficiency broke even at the earliest time.

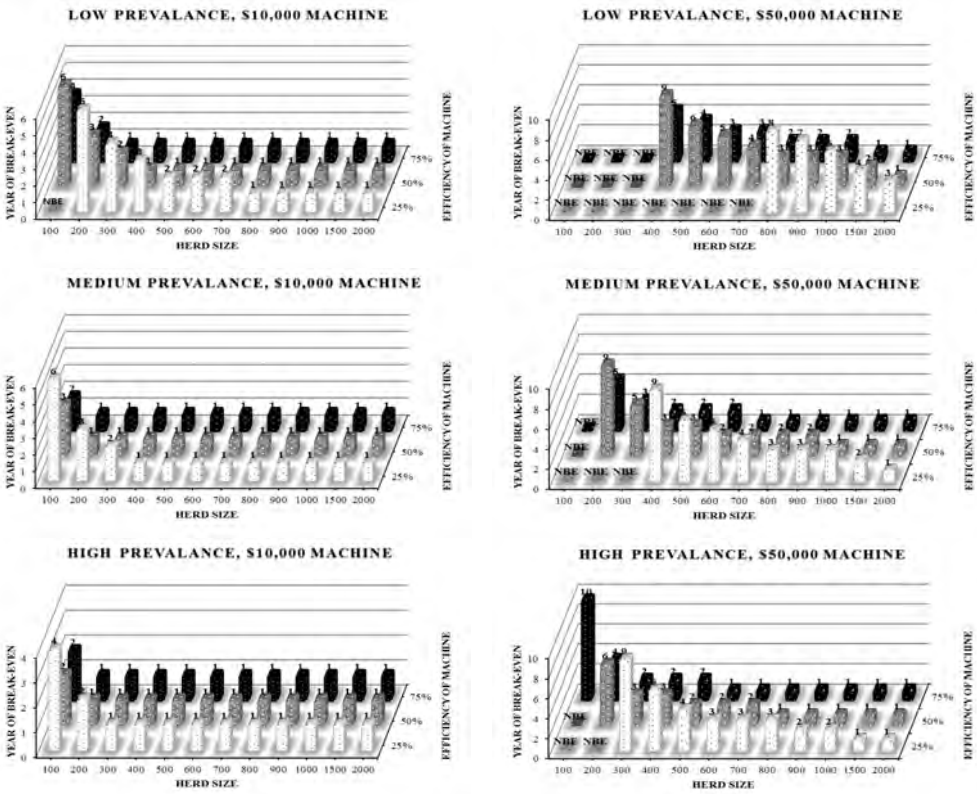

Figure 2. Year (number on top of each bar) in which investment in an automatic lameness detection machine (over a human detection system) breaks even, for a 10 year planning horizon at 12 different herd sizes and at three different prevalences of lameness (Low – subclinical (SC) (25%), clinical (C) (20%); Medium – SC (75%), C (43%); High – SC (125%), C (65%)) at three different lameness detection efficiencies (25%, 50% and 75% reduction in production losses as a result of earlier detection). Two different costs of machine ($10,000, and $50,000) were tested. A yearly maintenance cost of 10% of the cost of the machine was used as well. NBE (No break-even year) refers to the scenarios where investment in the machine did not break even during the 10 year planning horizon

Table 1. The effects of different rates of lameness prevalence (low, medium, high) on net return, lameness cases, % of lameness cases treated, average cost of lameness and average cost per case, following an optimal replacement policy

Lameness prevalence	% Reduction in Prod. Loss due to ALD[a]		Net return[b]	Lameness cases[c]	% of lameness cases treated[d]	Average cost of lameness (US$)	Average cost per case[e] (US$)	Yearly avoided cost in herd due to ALD ($)	Present value of 10 yr avoided cost in a 1,000 cow herd due to ALD ($)
Default		No lameness[e]	426.05						
	default	Both severe and moderate	388.12		95.90	37.93	192.54	0	0
(SC- 7%, C- 12%)[f]	25%		394.06	19.70	96.90	31.99	162.39	5,940	46,332
	50%		400.00		98.70	26.05	132.23	11,880	92,664
	75%		416.00		99.40	10.05	51.02	27,880	217,464
Low prevalence		No lameness[e]	426.05						
	default	Both severe and moderate	344.00		94.34	82.05	184.22	0	0
(SC- 25%, C- 20%)	25%		357.30	44.54	94.53	68.75	154.36	13,300	103,740
	50%		369.69		95.14	56.36	126.54	25,690	200,382
	75%		381.88		95.60	44.17	99.17	37,880	295,464
Medium prevalence		No lameness[e]	426.05						
	default	Both severe and moderate	231.00		93.14	195.05	156.04	0	0
(SC- 75%, C- 43%)	25%		257.40	125.00	94.37	168.65	134.92	26,400	205,920
	50%		283.44		95.06	142.61	114.09	52,440	409,032
	75%		308.82		95.45	117.23	93.78	77,820	606,996
High prevalence		No lameness[e]	426.05						
	default	Both severe and moderate	139.18		92.34	286.87	136.60	0	0
(SC- 125%, C- 65%)	25%		172.78	210.00	93.93	253.27	120.60	33600	262,080
	50%		206.00		94.91	220.12	104.82	66750	520,650
	75%		238.00		95.38	188.05	89.55	98820	770,796

[a]ALD: Automatic lameness detection system [b]Net returns in US$ per cow and year
[c]Incidence of lameness (cases per 100 cow years), [d]Percent of treated lame cows per all lame cows, [e]Average cost per lameness case

Conclusions

We used a dynamic programming model to estimate the average cost of lameness at both cow and herd level. The costs of lameness severities were dependent on the lameness induced production loss parameters used as inputs to the model. An operational framework which captured the complex interplay between the drivers affecting the economic value of automatic lameness detection systems was used to conduct a cost-benefit analysis of using such systems. A wide range of herd sizes, system efficiencies, system costs and lameness prevalences were tested. An investment in automatic lameness detection systems was justifiable in most of the scenarios investigated. Once more precise estimates of reduction in production losses due to the use of automatic lameness detection systems for different herds are available, more precise economic value estimation could be conducted by combining our customizable DP model and the operational framework used in this study.

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References

Barker, Z.E., Leach, K.A., Whay, H.R., Bell, N.J., Main, D.C. (2010). Assessment of lameness prevalence and associated risk factors in dairy herds in England and Wales. *Journal of Dairy Science,* 93: 932–941.

Bicalho, R.C., Warnick, L.D., Guard, C.L. (2008). Strategies to analyze milk losses caused by diseases with potential incidence throughout the lactation: a lameness example. *Journal of D*airy Science, 91: 2653–2661.

Booth, C.J., Warnick, L.D., Grohn, Y.T., Maizon, D.O., Guard, C.L., Janssen, D. (2004). Effect of lameness on culling in dairy cows. *Journal of D*airy Science, 87: 4115–4122.

Bruijnis, M.R.N., Hogeveen, H., and Stassen, E.N. (2010). Assessing economic consequences of foot disorders in dairy cattle using a dynamic stochastic simulation model. *Journal of Dairy Science,* 93: 2419–2432.

Cha E, Hertl, J.A., Bar, D., Grohn, Y.T. (2010). The cost of different types of lameness in dairy cows calculated by dynamic programming. *Prev. Vet. Med.,* 97: 1–8.

Enting, H., Kooij, D., Dijkhuizen, A.A., Huirne, R.B.N., and Noordhuizen-Stassen, E.N. (1997). Economic losses due to clinical lameness in dairy cattle. *Livest. Prod. Sci.* 49: 259–267.

Green, L.E., Hedges, V.J., Schukken, Y.H., Blowey, R.W., Packington, A.J. (2002). The impact of clinical lameness on the milk yield of dairy cows. *Journal of Dairy Science,* 85: 2250–2256.

Gröhn, Y.T., Wilson, D.J., Gonzalez, R.N., Hertl, J.A., Schulte, H., Bennett, G., Schukken, Y.H.. (2004). Effect of pathogen-specific clinical mastitis on milk yield in dairy cows. *Journal of Dairy Science,* 87: 3358–3374.

Hernandez J, Shearer, J.K., Webb, D.W. (2001). Effect of lameness on the calving-to-conception interval in dairy cows. *J. Am. Vet. Med. Assoc.,* 218: 1611–1614.

Hernandez, J.A., Garbarino, E.J. , Shearer, J.K., Risco, C.A., and Thatcher, W.T. (2005). Comparison of calving-to-conception interval in dairy cows with different degrees of lameness during the prebreeding postpartum period. *J. Am. Vet. Med. Assoc.,* 227: 1284–1291.

Kristensen, A.R. (2003). A general software system for Markov decision processes in herd management applications. *Comput. Electron. Agric.,* 38: 199–215.

Machado, V.S., Caixeta, L.S., McArt J.A.A., and Bicalho, R.C. (2010). The effect of claw horn disruption lesions and body condition score at dry-off on survivability, reproductive performance, and milk production in the subsequent lactation. *J. of Dairy Sci.,* 93: 4071–4078.

Warnick, L.D., Janssen, D., Guard, C.L., Gröhn, Y.T. (2001). The effect of lameness on milk production in dairy cows. *Journal of Dairy Science,* 84: 1988–1997.

Van De Gucht, T., Saeys, W., Van Nuffel, A., Pluym, L., Lauwers, L., Vangeyte, J., and Van Weyenberg, S. (2017). Farmers' preferences for automatic lameness-detection systems in dairy cattle. *Journal of Dairy Science*, 100: 5746–5757.

Van De Gucht, T., Saeys, W., Van Meensel, J., Van Nuffel, A., Vangeyte, J., and Lauwers. L. (2018). Farm-specific economic value of automatic lameness detection systems in dairy cattle: From concepts to operational simulations. *Journal of Dairy Science*, 101: 637–648.

Whay, H.R., Main, D.C.J., Green, L.E., and Webster, A.J.F. (2002). Farmer perception of lameness prevalence. 12th *International Symposium on Lameness in Ruminants*, Florida. pp. 355–358.

Is it possible to detect lame cows by analysing their footfall sounds?

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Abstract

Detection of lameness, which is commonly caused by diseases of the claws and limbs, is an important factor for animal welfare. The presented study is part of a project aiming to develop a system which is capable of an automated diagnosis of lameness in cattle by analysing their footfall sound. Data were generated from cows walking along a test track situated outside the stable where eight piezoelectric sensors recorded their walking speed and the footfall sound of their steps. Locomotion of the animals was scored and they were graded using a three-scale scoring system (LS1 = non-lame; LS2 = uneven gait; LS3 = lame). Subsequently, the cows were examined by a hoof trimmer. The mean walking speed at the test track was significantly higher in cows with LS1 (0.96 m/s) compared to animals with LS2 (0.76 ms-1) and LS3 (0.82 ms-1). The standard deviation of volume in the recorded footfall sound signal (SDFS) was considered as a factor for the force of cow's footsteps. Therefore, a higher value of SDFS describes an increased difference between a sound signal and no sound signal. Actually, cows with non-infectious diseases showed lower SDFS (0.017 dB) than healthy ones and those affected by infectious disease (both = 0.021 dB). This result confirmed the assumption, that in particular, cows with non-infectious diseases have a greater sensitivity to pain and demonstrate a less forceful respectively loudly gait pattern. These first findings clearly show the potential of footfall sound analysis for lameness detection.

Keywords: lameness detection, dairy cattle, acoustic analysis, footfall sound

Introduction

Lameness is a widespread health problem in dairy production and so an early detection is an important factor for animal welfare. Most commonly, lameness is caused by diseases of the claws and limbs (Van Nuffel *et al.*, 2015). In turn, these diseases cause pain to the animals and that leads to a change in their natural behaviour and their normal gait to reduce discomfort (Scott, 1989; O'Callaghan *et al.*, 2003; Ito *et al.*, 2010). As the cows try to relieve the affected and painful limb, they change the weight distribution by shifting their weight to a healthy leg. Furthermore, they take shorter and more careful steps. The assessment of locomotion is the most common method to detect lameness. But this visual observation is complicated, in particular, with the ever increasing size of dairy farms and the reduced time available for observing the cows (Pastell *et al.*, 2010). For this reason, there is growing interest in supporting automated methods to detect lameness.

Previous studies used the changes in the normal movement as mentioned above and, referring to this, developed various tools with the aim of improving the assessment of lameness. Kujala *et al.* (2008) analysed measurements of force sensors which recorded the weight on each leg while the cows were standing in the milking robot. Their system was particularly able to detect severely lame cows affected by non-infectious diseases such as sole ulcers and white line disease. As a major drawback they concluded that these force sensors need to be checked regularly and frequently need to be repaired. Maertens *et al.* (2011) analysed data from cows while walking over a force-sensitive mattress and presented a kinematic gait analysis. They suggested further research was required

concerning variables of asymmetry and speed for detecting lameness. Other approaches for gait analysis include computer vision concepts which use information from video recordings and evaluate movement patterns such as the distance of the hind hoof from the fore hoof position (Song *et al.*, 2008), the arching of cows back (Poursaberi *et al.*, 2010) or touch and release of the fetlock joint (Pluk *et al.*, 2012).

To our knowledge, currently no practical-systems for an automated diagnosis of claw lesions exist. Therefore, the aim of our study was to provide first insights into implementing a system which is capable of distinguishing healthy animals from those affected by claw lesions by analysing their footfall sound on farm (Volkmann *et al.*, 2019). Walking on a solid surface, as can be found in most cattle housings, produces footfall sound signals. It was hypothesised that this footfall sound varies in various parameters according to the gait of each animal. Therefore, in this study the parameters walking speed as well as differences in the maximum recorded volume of footfall sound (representing the weight loaded on each leg) were implemented and evaluated in detail in order to detect cows affected by claw lesions.

Material and methods

Data collection

The study was conducted in a free-stall barn where the lactating cows were housed in two sections. One section of the stall consisted of slatted flooring and was equipped with a milking robot. The other section was a deep straw barn and the cows were milked twice a day in a milking parlour. The experimental set-up was placed outside the stable with a 22 m long test track which was partly covered with three elements of slatted floor. In the middle of the three slatted floor elements (length: 3.1 m; wide: 0.8 m) eight piezoelectric sensors (ICP accelerometer; PCB Group Inc., New York, USA) were attached and the signals of the footfall sound of the cows were recorded with a measuring device from IMC® (imc CS-3008-N, imc Messsysteme GmbH, Berlin, Germany) with a frequency of 50 kHz. The raw sound files were edited using the IMC® Famos Signal Analysis 7.0 software and passed through a filtering process. The main focus of this filtering process was the detection of the steps and the differentiation of step events from the background noise of the entire experimental set-up. At the end of the described test track, the weight of each cow was measured with a weighing platform (ID5000, Tru-Test Limited, Alberta, Canada). To habituate the cows to this new gangway they had to pass the test track at least twice. After the trial runs, all lactating cows walked consecutively along the test track, their footfall sound was recorded and they were filmed laterally by video (Camcorder GC-PX100BE, JVC KENWOOD Corporation, Kanagawa, Japan). Simultaneously, the animals were rated by a trained observer with a previously validated three-stage locomotion scoring system (Volkmann *et al.*, 2018). Animals with a confident walk and a perfect gait pattern were rated with score 1 (LS1). Cows with a slightly asymmetric gait and unequal weight-bearing were assessed with score 2 (LS2). Clearly lame animals on one (or more) limbs were given score 3 (LS3). Three days after recording and locomotion scoring, the hooves were examined by a professional hoof trimmer. All diagnostic findings concerning claw disorders were directly recorded in accordance with the key code of the German Agricultural Society (DLG, 2014). Afterwards, on the basis of the diagnosed type of diseases from all four legs, the animals were grouped according to the three-level system as follows:

- Group 0: cows without any disease,
- Group 1: cows affected by non-infectious disease,
- Group 2: cows affected by infectious disease.

If the cows were affected by both infectious and non-infectious diseases, they were rated with regard to the severity of the disease and, subsequently, grouped concerning the claw lesion with the higher severity.

Statistical analysis

Statistical analysis was performed using SAS 9.4 (SAS Institute Inc., Cary, NC, USA). The variable walking speed (WS) and the standard deviation of volume in the recorded footfall sound (SDFS) were tested for normal distribution to select a suitable statistical procedure. Afterwards, WS and SDFS were analysed with a general linear mixed model (PROC GLIMMIX) considering the potential influencing factors: group of housing (section 1 vs section 2), parity number (1 - 6), bodyweight, locomotion score (LS1, LS2, LS3) and type of disease (Group 0, 1, and 2). Multiple comparisons of least squares means (LSMEANS) were performed using the post-hoc Tukey test. The results of the statistical tests were considered to be significant at *P-values* < 0.05.

Results and discussion

Installing the test track outside the stable offered the advantage of having a straight alley for observation and recording. However, this arrangement also resulted in an increased agility of the cows, even though they had been acclimatised to the test track in advance. Thus, data of cows stopping, running or jumping on the measurement zone had to be deleted, as this resulted in errors. Overall, data were generated from 144 animals, but the footfall sound of 76 animals (housing section 1: n = 36 and housing section 2: n = 40) was considered as useful and was analysed. Although, in other studies, two days were sufficient for an adaption to the test track (Flower *et al.*, 2007), the habituation phase in our study was not long enough. The analysed cows in the present study reached an average parity of three (min = 1; max = 6) and an average bodyweight of 685 kg (min = 538 kg; max = 880 kg).

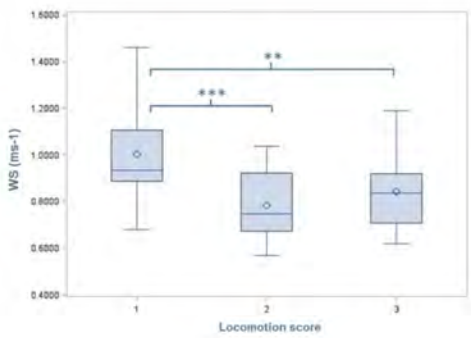

Figure 1. Mean walking speed (WS) of the cows with regard to the degree of rated locomotion score. Level of statistical significance between the LSMEANS is indicated by the number of asterisks (** < 0.01; *** < 0.001)

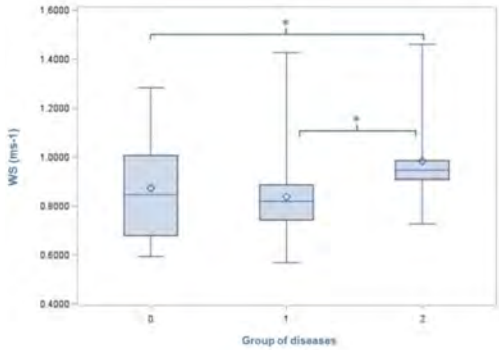

Figure 2. Mean walking speed (WS) of the cows with regard to the diagnosed type of diseases (group 0 = no diseases; group 1 = non-infectious diseases; group 2 = infectious diseases). Level of statistical significance between the LSMEANS is indicated by the number of asterisks (* < 0.05)

The average time for passing the measuring section was 3.68 s (min = 2.12 s; max = 5.46 s; SD = 0.75 s). Accordingly, the cows covered the distance of the test track of 3.1 m at a walking speed (WS) of 0.84 ms-1. This result exactly corresponds to the speed on concrete floor, measured in the morning, in the study of Zillner *et al.* (2018). But the walking speed is generally slower than in other studies. Telezhenko and Bergsten (2005), who compared

the speed on different floor types, determined a walking speed of 0.97 ms-1 on slatted concrete floor and Chapinal *et al.* (2010) even measured 1.42 ms-1 in non-lame cows. These differences may result from varying recording methods or the missing human escort walking behind the cows to encourage them. A further explanation for the reduced speed in the present study can probably be found in the low motivation of the cows to return to the stable after milking to start with feed and water intake. In our study, the cows had to walk the test track in the morning, but two hours after the morning milking.

The mean WS was significantly affected by the rated locomotion score ($P = 0.0001$) and the type of claw lesion ($P = 0.0466$). The comparisons of LSMEANS showed differences between LS1 (0.96 ms-1) and LS2 (0.76 ms-1) ($P \leq 0.0001$) as well as between LS1 (0.96 ms-1) and LS3 (0.82 ms-1) ($P = 0.0062$), whereby the cows rated with LS1 were the fastest ones (Figure 1). This result confirms the findings of the locomotion score, with animals with lower score representing a smooth as well as faster gait pattern and it corresponded to results by Chapinal *et al.* (2009). They reported that walking speed is negatively correlated with the numerical gait score. Moreover, they considered that it is difficult to state whether gait changes are a consequence of slow gait or impaired gait results at a slow pace.

Cows affected by non-infectious diseases like sole ulcers (0.81 ms-1) showed a slower walk than those without diseases (0.83 ms-1) ($P = 0.5649$) and those with infectious disease (0.96 ms-1) ($P = 0.0146$) (Figure 2). Accordingly, Flower *et al.* (2005) measured shorter strides and reduced speed of cows with sole ulcers compared to healthy animals. Likewise, gait alterations in general – changes in walking speed included – were more evident in cows with sole ulcers than in animals without any lesion (Blackie *et al.*, 2013).

The mean standard deviation of volume in the recorded footfall sound signal (SDFS) was 0.019 dB (min = 0.009 dB; max = 0.049 dB; SD = 0.007 dB). The higher this value was, the louder the difference between a footfall sound signal and no signal. SDFS was affected by the locomotion score ($P = 0.0014$) and the comparisons of LSMEANS showed significant differences between LS1 (0.024 dB) and LS2 (0.017 dB) ($P = 0.0032$) as well as between LS1 (0.024 dB) and LS3 (0.018 dB) ($P = 0.0060$), with animals classified to the non-lame ones (LS1) showing the highest SDFS (Figure 3). Accordingly, Maertens *et al.* (2011) found that all kinematic variables differed between the given gait scores. These kinematic variables from their study also described nothing but cows' locomotion by measuring, for example, stride length, abduction, step overlap or asymmetry. Hence, it is quite explicable that the average SDFS in our study was different between the levels of locomotion score.

Furthermore, the variable 'types of diseases' tended to have an influence on SDFS with $P = 0.0721$. The comparisons of LSMEANS revealed that animals with non-infectious diseases (Group 1 = 0.0017 dB) showed significantly lower SDFS ($P = 0.0366$) than cows without any disease (Group 0 = 0.021 dB) (Figure 4). Our findings support previous results showing claw lesions to affect the way cows distribute their weight on the affected respectively healthy leg (Pastell and Kujala, 2007; Rushen *et al.*, 2007). Furthermore, these results support the statement of Passos *et al.* (2017) that especially non-infectious diseases, such as sole ulcers, have clear impacts on the strain on limbs and particularly cows affected by non-infectious diseases have a greater sensitivity to pain. These lame cows adopt the best compensatory movements to minimise their pain and, therefore, show less variation in their movement (Blackie *et al.*, 2013). The findings from the presented study confirm that with decreasing SDFS.

In summary, with SDFS in the recorded signal interpreted as a variable for the loudness or weight load of cows' footstep, these first results clearly show the potential of footfall sound analysis for lameness detection.

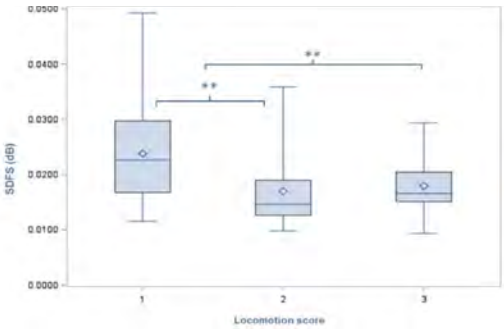

Figure 3. Mean standard deviation of volume in the footfall sound (SDFS) with regard to the degree of rated locomotion score. Level of statistical significance between the LSMEANS is indicated by the number of asterisks (** < 0.01)

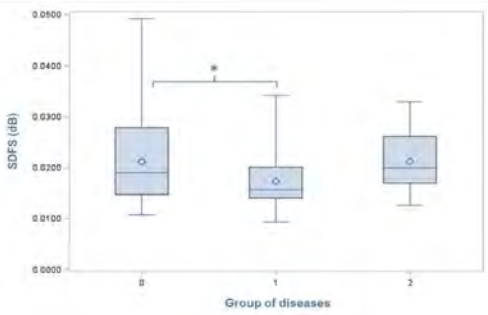

Figure 4. Mean standard deviation of volume in the footfall sound (SDFS) with regard to the diagnosed type of diseases (group 0 = no diseases; group 1 = non-infectious diseases; group 2 = infectious diseases). Level of statistical significance between the LSMEANS is indicated by the number of asterisks (* < 0.05)

However, the performance of the system has to be validated with more cows and on other farms, where the system could be installed inside the stable (e.g. on the way back from the milking parlour). Also, further work is required to assess the footfall sound of cows concerning the number and uniformity of their steps to improve analysing the recorded signal. Moreover, it should be noted that for this first practical approach only one data set was examined using the method of mean comparison. To improve the evaluation of this method in terms of lameness detection, more parameters should be considered.

Conclusions

As visual monitoring of locomotion on farm is time-consuming and, thus, cost inefficient, the aim of the presented study was to develop a system which is capable of detecting claw lesions in dairy cows on farm by analysing their footfall sound. This current investigation shows that the used measurement installation can record cows' individual footfall sound without any noise interference. The analyses of the recorded sounds can be used to successfully distinguish between cows without claw lesions and those animals affected by non-infectious disease, which are considered as particularly painful ones. Further research is required on this system to improve the measurements on a farm and especially a more detailed interpretation of the recorded footfall sounds.

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References

Blackie, N., Bleach, E.C.L., Amory, J.R., and Scaife, J.R. (2013). Associations between locomotion score and kinematic measures in dairy cows with varying hoof lesion types. *Journal of Dairy Science*, 96: 3564–3572.

Chapinal, N., de Passille, A.M., Weary, D.M., von Keyserlingk, M.A.G., and Rushen, J. (2009). Using gait score, walking speed, and lying behavior to detect hoof lesions in dairy cows. *Journal of Dairy Science*, 92: 4365–4374.

DLG (2014). Klauengesundheit beim Rind. aid Infodienst Ernährung, Landwirtschaft, Verbraucherschutz e.V. , Bonn.

Flower, F.C., Sanderson, D.J., and Weary, D.M. (2005). Hoof pathologies influence kinematic measures of dairy cow gait. *Journal of Dairy Science*, 88: 3166–3173.

Flower, F.C., de Passille, A.M., Weary, D.M., Sanderson, D.J., and Rushen, J. (2007). Softer, higher-friction flooring improves gait of cows with and without sole ulcers. *Journal of Dairy Science*, 90: 1235–1242.

Ito, K., von Keyserlingk, M.A.G., LeBlanc, S.J., and Weary, D.M. (2010). Lying behavior as an indicator of lameness in dairy cows. *Journal of Dairy Science,* 93: 3553–3560.

Kujala, M., Pastell, M., and Soveri, T. (2008). Use of force sensors to detect and analyse lameness in dairy cows. *The Veterinary Record*, 162: 365–368.

Maertens, W., Vangeyte, J., Baert, J., Jantuan, A., Mertens, K.C., De Campeneere, S., Pluk, A., Opsomer, G., Van Weyenberg, S., and Van Nuffel, A. (2011). Development of a real time cow gait tracking and analysing tool to assess lameness using a pressure sensitive walkway: The GAITWISE system. *Biosystems Engineering*, 110: 29–39.

O'Callaghan, K.A., Cripps, P.J., Downham, D.Y., and Murray, R.D. (2003). Subjective and objective assessment of pain and discomfort due to lameness in dairy cattle. *Animal Welfare,* 12: 605–610.

Passos, L.T., da Cruz, E.A., Fischer, V., da Porciuncula, G.C., Werncke, D., Dalto, A.G.C., Stumpf, M.T., Vizzotto, E.F., and da Silveira, I.D.B. (2017). Dairy cows change locomotion score and sensitivity to pain with trimming and infectious or non-infectious lesions. *Tropical Animal Health and Production*, 49: 851–856.

Pastell, M.E., and Kujala, M. (2007). A probabilistic neural network model for lameness detection. *Journal of Dairy Science*, 90: 2283–2292.

Pastell, M., Hanninen, L., de Passille, A.M., and Rushen, J. (2010). Measures of weight distribution of dairy cows to detect lameness and the presence of hoof lesions. *Journal of Dairy Science*, 93: 954–960.

Pluk, A., Bahr, C., Poursaberi, A., Maertens, W., van Nuffel, A., and Berckmans, D. (2012). Automatic measurement of touch and release angles of the fetlock joint for lameness detection in dairy cattle using vision techniques. *Journal of Dairy Science*, 95, 1738–1748.

Poursaberi, A., Bahr, C., Pluk, A., Van Nuffel, A., and Berckmans, D. (2010). Real-time automatic lameness detection based on back posture extraction in dairy cattle: Shape analysis of cow with image processing techniques. *Computers and Electronics in Agriculture,* 74: 110–119.

Rushen, J., Pombourcq, E., and de Passille, A.M. (2007). Validation of two measures of lameness in dairy cows. *Applied Animal Behaviour Science*, 106: 173–177.

Scott, G.B. (1989). Changes in limb loading with lameness for a number of Friesian cattle. *British Veterinary Journal* 145: 28–38.

Song, X.Y., Leroy, T., Vranken, E., Maertens, W., Sonck, B., and Berckmans, D. (2008). Automatic detection of lameness in dairy cattle - Vision-based trackway analysis in cow's locomotion. *Computers and Electronics in Agriculture*, 64: 39–44.

Telezhenko, E., and Bergsten, C. (2005). Influence of floor type on the locomotion of dairy cows. *Applied Animal Behaviour Science*, 93: 183–197.

Van Nuffel, A., Zwertvaegher, I., Pluym, L., Van Weyenberg, S., Thorup, V.M., Pastell, M., Sonck, B., and Saeys, W. (2015). Lameness Detection in Dairy Cows: Part 1. How to Distinguish between Non-Lame and Lame Cows Based on Differences in Locomotion or Behavior. *Animals,* 5: 838–860.

Volkmann, N., Stracke, J., and Kemper, N. (2018). Evaluation of a gait scoring system for cattle by using cluster analysis and Krippendorff's α reliability. *The Veterinary Record,* doi:10.1136/vr.105059.

Volkmann, N., Kulig, B., and Kemper, N. (2019). Using the footfall sound of dairy cows for detecting claw lesions. *Animals (Basel)*., 9(3): 78. Published 2019 Mar 1. doi:10.3390/ani9030078.

Zillner, J.C., Tücking, N., Plattes, S., Heggemann, T., and Büscher, W. (2018). Using walking speed for lameness detection in lactating dairy cows. *Livestock Science*, 218: 119–123.

Effect of administration of ketoprofen on locomotion characteristics and weight distribution in cattle with limb pathologies

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Abstract

Pain assessment is a key component to evaluate and a prerequisite to improve cattle welfare. Therefore, alleviating pain is becoming an increasingly important aspect in routine veterinary practice. This study aimed at measuring the effect of ketoprofen in cattle affected with limb pathologies during the time period when ketoprofen is thought to be active (24 h). Gait scoring and validated automated tools of weight bearing and gait analysis were used for evaluation. A single administration of ketoprofen significantly reduced the differences across limbs at walking and standing one hour after being administered, but no longer after 18 hours.

Key words: cattle, ketoprofen, limb pathologies, pain, welfare

Introduction

Cattle lameness is a painful disorder, with an important welfare and economic impact. As cattle are prey species with a stoic character, they rarely show overt signs of pain until the stimulus is severe. Therefore, recognition and assessment of pain in cattle remain challenging (Coetzee, 2013). Cattle practitioners, as well as claw trimmers and farmers, might underestimate the sensitivity of pain in cattle compared to other species (Becker *et al.,* 2013). Consequently, valid and reliable methods for pain assessment of the locomotor apparatus in cattle are needed. Foot pathologies induce a hyperalgesic state and produce a range of inflammatory mediators at the site of the pathology, including the release of prostaglandins, thromboxanes and leukotrienes. Ketoprofen was shown to moderately reduce hyperalgesia of lame cows in the recovery period after therapeutic claw trimming (Whay *et al.,* 2005), improving the weight distribution between sound and lame legs (Flower *et al.,* 2008) and decreasing the weight shifting across the rear legs (Chapinal *et al.,* 2010; Novak *et al.,* 2016). The newly developed tools for objectively assessing the cows' gait represent a promising approach to detect cows with foot pathologies and even very slight cases of lameness (Nechanitzky *et al.,* 2016; Alsaaod *et al.,* 2017). Therefore, the aim of this study was to evaluate the effect of the NSAID Ketoprofen (Rifen® Streuli AG, Switzerland) during the time period when ketoprofen is thought to be active (24 h) on cows affected with limb pathologies using gait scoring and validated automated tools of weight bearing and gait analysis.

Material and methods

Ethics statement:

The study protocol was approved by the animal experimentation committee of the canton of Bern, Switzerland (permission #25601).

Animals and inclusion criteria

A total of 41 lame cattle referred to the clinic for Ruminants, Vetsuisse-Faculty, University of Bern, Switzerland, were included in this study. The inclusion criteria for the study animals were: cattle with unilateral fore- or hindlimb lameness, referred to the clinic for further assessment of this health problem. Cattle must not exhibit any relevant systemic concentration of analgesics at the beginning of the study. "No relevant systemic

concentration of analgesics" was defined as those animals with an analgesic pre-treatment less than 4.5 × the elimination half-life time ago.

Data collection

The study was performed as blinded, randomised, and placebo-controlled clinical trial. Cattle were randomly allocated to either the ketoprofen (group K; n = 21) or placebo group (group P; n = 20), receiving one dose of ketoprofen (3 mg/kg of BW i.v.; Rifen® Streuli Pharma AG, Switzerland, http://www.streuli-pharma.ch/) or an equivalent volume of sterile isotonic saline solution (NaCl 0.9% steril® Laboratorium Dr. G. Bichsel, Interlaken-Switzerland), respectively. Three data collection time points - before treatment (basis; T0), one hour (hr) after treatment (T1) and 18 hours (hrs) after treatment (T2) were defined. The locomotion was scored using a one to five numerical rating system, where 1 = non-lame and 5 = severely lame; (Flower and Weary, 2006). The weight distribution parameters (weight distribution and SD of the weight derived from a 4-scale weighing platform as described by Nechanitzky *et al.,* 2016). The platform consisted of four recording units (0.78 × 0.55 m), with one hermetically sealed load cell each (HBM, Hottinger Baldwin Messtechnik AG, Volketswil, Switzerland) and covered with individual rubber mats of 1 cm thickness. Cattle were given 5–10 minutes to get used to standing quietly on the balance. When they were standing with each limb positioned on the appropriate unit, the weight measurement was started manually. Total data collection time was five minutes at a frequency of 10 Hz and the weight of the four limbs measured independently.

The cows were equipped with two stand-alone 3D accelerometers (400 Hz; USB Accelerometer X16-4; Gulf Coast Data Concept, Waveland, USA), which were fitted at the level either of both metatarsi or both metacarpi, depending on the location of the pathology. The gait variables of the cow pedogram (kinematic outcome = stance phase duration; kinetic outcome = foot load and toe-off) were extracted, using the validated Cow-Gait-Analyzer as described by Alsaaod *et al.,* 2017.

Statistical analyses

Data analysis was performed at the cow level, and all included variables that represented the difference across the contralateral limbs of the affected limb pair, and the measurements at 1 hr and 18 hrs were compared to the baseline. A repeated measures ANOVA was used to determine the differences between groups K and P. All variables including locomotion scores were considered as "continuous variables" to perform the ANOVA. A Bonferroni corrected P-value was calculated; the significance value was set at $P \leq 0.05$ (without Bonferroni adjustment). The variables were analysed using the software package NCSS10 (NCSS LLC, Kaysville, UT).

Results and discussion

At T1 only the relative stance phase duration and the weight distribution showed significant differences between group K (mean ± SD; 3.85 ± 5.77 and 7.76 ± 7.95) and group P (-1.51 ± 2.94 and 0.827 ± 8.6) (P = 0.001 and 0.002), respectively. Group K had significantly lower differences across the contralateral limbs at T1 as compared to group P. However, neither the gait variables nor the weighing platform variables showed differences between group K and P at T2. Ketoprofen was reported as rapidly exiting the bloodstream to enter the tissue compartment at the site of inflammation, where it is pharmacologically active (Landoni *et al.*, 1995). An effect of ketoprofen on locomotion scores was not found. The results of locomotion scores support previous findings, which reported that the objective assessment of gait, weight bearing and activity has been shown to be more sensitive than gait scores as a method of evaluating the effect of ketoprofen (Chapinal *et al.,* 2010).

The results of this study reveal that measuring stance phase duration of the cow

pedogram while cows are walking and weight bearing across limbs while standing show great potential as automated methods for evaluating the effect of NSAIDs on motion and weight bearing characteristics of the musculoskeletal apparatus of lame cattle.

Conclusions

A combination of stance phase duration at walking and weight distribution at standing was the best set of parameters to determine the effect of ketoprofen. A single administration of ketoprofen significantly reduced the differences across the limbs at walking and standing after one hour of administration, but this effect was not detectable after 18 hrs. It must be mentioned that treatment of foot disorders should not be restricted to administration of NSAIDs but focus on early treatment of the cause of lameness. Otherwise, deterioration of the primary disease and overload of the affected limb will be supported.

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References

Alsaaod, M., M. Luternauer, J.T. Hausegger, R. Kredel, and Steiner, A. (2017). The cow pedogram – analysis of the gait cycle variables allows for detection of lameness and foot pathologies. *Journal of Dairy Science,* 100(2): 1417–1426.

Becker, J., M. Reist, K. Friedli, D. Strabel, M. Wuthrich, and Steiner, A. (2013). Current attitudes of bovine practitioners, claw-trimmers and farmers in Switzerland to pain and painful interventions in the feet in dairy cattle. *The Veterinary Journal,* 196(3): 467–476.

Chapinal, N., A.M. de Passille, J. Rushen, and Wagner, S. (2010). Automated methods for detecting lameness and measuring analgesia in dairy cattle. *Journal of Dairy Science*, 93(5): 2007–2013.

Coetzee, J.F. (2013). *Assessment and Management of Pain Associated with Castration in Cattle. Veterinary Clinics of North America: Food Animal Practice,* 29(1): 75–101.

Flower, F.C., and D.M. Weary (2006). Effect of hoof pathologies on subjective assessments of dairy cow gait. *Journal of Dairy Science*, 89(1): 139–46.

Flower, F.C., M. Sedlbauer, E. Carter, M.A.G. von Keyserlingk, D.J. Sanderson, and Weary, D.M. (2008). Analgesics improve the gait of lame dairy cattle. *Journal of Dairy Science,* 91(8): 3010–3014.

Landoni, M.F., and Less, P. (1995). Pharmacokinetics and pharmacodynamics of ketoprofen enantiomers in calves. *Chirality,* 7(8): 586–97.

Nechanitzky, K., A. Starke, B. Vidondo, H. Muller, M. Reckardt, K. Friedli, and Steiner, A. (2016). Analysis of behavioral changes in dairy cows associated with claw horn lesions. *Journal of Dairy Science,* 99(4): 2904–2914.

Novak, B.L., B.H., Manning, J.S., Tena, and Wagner, S.A. (2016). Behavioral evaluation of the analgesic effects of ketoprofen in lame dairy cows. *Proceedings, American Association of Bovine Practitioners 49th Annual Meeting*, New Orleans, Louisiana, 155.

Whay, H.R., A.J.F. Webster, and Waterman-Pearson, A.E. (2005). Role of ketoprofen in the modulation of hyperalgesia associated with lameness in dairy cattle. *Veterinary Record,* 157(23): 729–737.

Effect of body posture on respiration rate, heart rate and rectal temperature of dairy cows under thermoneutral conditions

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Abstract

The present study aimed to investigate the influence of body posture on the physiological traits in lactating dairy cows under thermoneutral conditions. Data were collected from 137 lactating Holstein Friesian dairy cows (1st to 8th lactation; 40.7 ± 6.8 kg milk per day and 132.6 ± 70.4 days in milk) housed in a loose, naturally ventilated barn from June 2015 to December 2016. Respiration rate (RR, hourly visually counted), heart rate (HR, twice a day by stethoscope), and rectal temperature (RT twice a day measured with a veterinary digital thermometer) were used as physiological traits. Cow body posture (standing vs lying) was documented during the data collection. Data were analysed for differences between factor levels with repeated measurements of linear mixed models ($\alpha = 0.05$). Lying cows had higher ($P < 0.001$) RR (34.22 ± 0.31 breaths per min; bpm) and HR (85.07 ± 2.23 beats per min) than standing cows (RR: 29.16 ± 0.23 bpm, HR: 82.33 ± 2.27 beats per min). Body postures influenced RR and HR, but not the RT of lactating dairy cows under thermoneutral conditions. Ongoing studies with an automatic RR sensor showed a positive correlation between visual and automatic counted RR in lying ($r = 0.98$) and standing cows ($r = 0.99$). Continuous measurements of RR with an automatic sensor deliver reliable data from the cows.

Keywords: dairy cow, naturally ventilated barn, standing cow, lying cow, automatic sensor

Introduction

Atmospheric conditions are major contributors to animal stress in warm and temperate climate zone conditions (Legates *et al.,* 1991). Some environmental parameters such as temperature, relative humidity which determine the temperature-humidity index (THI) have been investigated to identify their effects on cow performance by establishing critical ambient temperatures for dairy cows (Thom, 1959, West, 2003). It is well documented that the optimal temperature range for dairy cows should be between -0.5–20 °C (Hahn, 1999) or for THI values to be below 68 (Zimbelman and Collier, 2011).

Physiological parameters such as respiration rate (RR), heart rate (HR), and body temperature have been demonstrated as adequate and timely indicators of heat stress in dairy cows (Kadzere *et al.*, 2002, Moallem *et al.*, 2010, Costa *et al.*, 2015a). Among other major physiological parameters consulted in the literature, RR and body temperature have long been used as a heat stress indicator (Gaughan *et al.,* 2000, Brown-Brandl *et al.*, 2005, Galán *et al.,* 2018). However, RR increases earlier than rectal temperature (RT) in cows under hot conditions, and a cow's breathing is the earliest response to fluctuating air temperatures (Ferreira *et al.*, 2006, Moallem *et al.,* 2010, Costa *et al.,* 2015b). An increase in RR allows a cow to initiate heat dissipation before a significant increase in its body temperature and the subsequent changes in normal body functions occurs (Berman, 2005).

Individual cows' reactions in susceptibility to hot conditions are challenging the identifying of adequate thresholds of heat stress, which are necessary to implement adequate measures to assume a real stress level. Gaughan *et al.* (2000) affirmed that animal-factors

as age, sex, genotype, performance, nutrition, time of feeding, body condition, as well as previous exposure to hot conditions influence directly the RR of cattle.

If changes in RR can be detected early, targeted measures can be taken to alleviate the strain on the animal and thus prevent performance losses and increase the animal welfare. The RR is considered as a well suited cow parameter for heat stress, however, the common method to count the flank movements visually in cattle is time-consuming and labour-intensive (Brown-Brandl *et al.*, 2005, Milan *et al.,* 2016).

The aim of the present study was to identify responses of respiration rate, heart rate and rectal temperature in lactating dairy cows regarding their body posture under thermoneutral conditions. In a further study, the correlation between visual and automatic RR sensor considering body posture of cows was evaluated.

Materials and methods

Animals, housing and management

The present study was conducted on the dairy farm of the Agricultural Research and Education Center for Animal Breeding and Husbandry "Gross Kreutz" in Brandenburg, Germany (coordinates: 52°23'47.4"N, 12°46'02.8"E, approximately 56 km west of Berlin, 32 m above sea level). The climate of this region is predominantly continental.

The data were collected from June 2015 to December 2016. The data were collected with max 30 Holstein Friesian lactating dairy cows per day. During the measurements, the health status of the cows was constantly evaluated by a veterinarian who selected only healthy cows for the measurements. A total of 137 cows from first to eighth lactation were included during the whole experimental period. The cows were milked three times a day by an automatic milking system (AMS, Lely Astronaut A4, Maassluis, the Netherlands).

The animals were housed in a naturally ventilated barn, as already used by Heinicke *et al.* (2018) and by Hempel *et al.* (2018), aligned in an NE-SW orientation with a floor area of 686 m^2 (13.7 m^2 per cow). The feeding alley was 27.7 m long (animal:feeding place ratio of 1:1). The herd size in this barn was on average 50 animals. The cows were fed a totally mixed ration twice a day. Additional concentrate was fed in the AMS based on individual DIM and milk yield. The cows had access to 51 lying cubicles with deep straw bedding, 34 of them were arranged in a double row and 17 in a single row. An automatic scraper removed manure from the concrete walking alleys approximately once per hour. The waiting area in front of the AMS had a slatted floor.

Animal parameters

The physiological parameters were measured between 07.00 h to 15.00 h (GMT + 01.00 h). The time of the data collection was chosen to comprise a representative range from low to high ambient temperatures during the day period. Datasets were collected during the experimental period, with up to three measurement days per week. The RR was hourly observed visually by counting right thoracoabdominal movements for 30 seconds and multiplying the value by two (i.e. breaths per minute, bpm). The heart rate (HR) was measured twice a day using a stethoscope between fourth and sixth intercostal spaces in the breastbone region for 15 seconds and multiplying the value by four (i.e. beats per min). The rectal temperature (RT) was taken twice a day using a veterinary digital thermometer (Microlife VT 1831, Microlife Corporation, Taipei, Taiwan; range between 32–44.9 °C), and obtained directly from rectal wall. Cow body posture (i.e. standing vs lying) was documented during the data collection.

Environmental measurements

Ambient temperature (AT) and relative humidity (RH) of the air in the barn were recorded every five minutes with eight data loggers (EasyLog USB 2+, Lascar Electronics Inc., Whiteparish, England) positioned at eight locations inside the building at 3.4 m above the floor. The temperature-humidity index (THI) was calculated according to NRC (1971) as follows:

$THI = (1.8 \times T_{db} + 32) - (0.55 - 0.0055 \times RH) \times (1.8 \times T_{db} - 26)$ where T_{db} is dry bulb temperature (in °C) and RH is relative humidity (in %).

Ambient temperature was classified in six different classes as follows: $-5 \leq AT < 0$, class 1; $0 \leq AT < 5$, class 2; $5 \leq AT < 10$, class 3; $10 \leq AT < 15$, class 4; $15 \leq AT < 20$, class 5 and $20 \leq AT < 23$, class 6.

Automatic RR sensor

A device, based on a differential pressure sensor with a microcontroller that can record RR automatically has been developed to make continuous long-term studies possible (Figure 1, for further description see Strutzke *et al.,* 2019). The reference method used was counting the flank movements of a total of six Holstein-Friesian cows. The rear flank movements of each cow were recorded by a camera and counted independently of the device by an observer. Eight videos of one minute each were recorded per cow. The data analysis was done with cows in three different body postures: dozing, lying, and standing. A total of 48 RR measurements of the device were compared with the counted RR frequencies of the video recordings.

Figure 1. Cow with sensor device attached

Statistical analyses

Physiological parameters (RR, HR and RT) were considered as dependent variable. Each cow was required to have at least 10 test-day records to be part of the analysis. The data collected used in the analyses comprehend ambient temperatures between -5 – 23 °C during the experimental period considered under thermoneutral condition in dairy cows (Spiers *et al.,* 2004). A regression analysis of RR, HR and RT as function of ambient

temperature was performed separately for standing and lying cows. The experimental design was completely randomized 5% and tested by ANOVA at significance level of 0.05. When ANOVA revealed a significant difference in least-square means, a Tukey-Kramer multiple comparisons test was performed at $P < 0.05$. Ambient temperature was classified in six different classes as described above. A linear mixed model with repeat measurements for each cow was used to test the influences of the ambient temperature and cow-related factors (body posture, lactation number and DIM) on physiological parameters. The fixed factors in the model were ambient temperature classes and body posture. The interaction between body posture and ambient temperature classes was also included. To assess the strength of the statistical relationship between the RR generated by the sensor data and the visual observation data, a Bravais-Pearson correlation analysis was conducted. To describe the agreement between the visual observation and the sensor data, a matched pair analysis was performed, which includes a Tukey mean-difference plot and the results of a paired t-test.

Results and discussion

Environmental parameters

Table 1 shows mean values of relative humidity and calculated THI in different classes of ambient temperature. Mean values of AT, RH and THI during the thermal neutral conditions were 13.91 ± 6.09, 82.69 ± 13.85 and 56.64 ± 10.18 (mean ± SD), respectively. The environmental conditions for an efficiently dairy production in cows range between -0.5–20 °C (Hahn, 1999) or THI values below of 68 (Zimbelman and Collier, 2011). In a study with high-yielding dairy cows, the THI considered as thermoneutral conditions was set between 55–61 (Garner *et al.*, 2017).

Table 1. Relative humidity (RH, in %) and temperature-humidity index (THI) according ambient temperature (AT, in °C) classes

AT classes	RH – Mean ± SD	THI - Mean ± SD
-5 ≤ AT < 0	94.96 ± 0.27	28.73 ± 0.26
0 ≤ AT < 5	96.02 ± 0.29	37.85 ± 0.08
5 ≤ AT < 10	91.47 ± 0.23	46.72 ± 0.08
10 ≤ AT < 15	84.22 ± 0.38	54.44 ± 0.09
15 ≤ AT < 20	81.02 ± 0.24	63.86 ± 0.05
20 ≤ AT < 23	62.73 ± 0.48	66.80 ± 0.03

Animal-related parameters

The dataset of 5,281 animal observations from a total of 137 cows during the whole experimental period was included into the model. Table 2 shows the mean RR, HR and RT of cows in different ambient temperature categories; and the comparison of the physiological parameters in standing vs lying body posture.

Table 2. Respiration rate (RR, breaths per min); heart rate (HR, beats per min) and rectal temperature (RT, °C) of cows depending on different ambient temperature (AT) classes and body postures

AT classes	Mean ± SE		
	RR	HR	RT
-5 ≤ AT < 0	22,50 ± 0.51	79,32 ± 1.08	37,85 ± 0.08
0 ≤ AT < 5	27,09 ± 0.28	80,58 ± 0.96	38,21 ± 0.03
5 ≤ AT < 10	29,78 ± 0.23	82,69 ± 0.47	38,25 ± 0.02
10 ≤ AT < 15	33,03 ± 0.26	82,15 ± 0.48	38,30 ± 0.02
15 ≤ AT < 20	36,04 ± 0.19	80,31 ± 0.32	38,31 ± 0.01
20 ≤ AT < 23	38,63 ± 0.38	82,27 ± 0.47	38,33 ± 0.02
P-value	*P < 0.001*	*NS*	*NS*
Body Posture			
Standing	29.16 ± 0.23	82.33 ± 2.27	38.07 ± 0.13
Lying	34.22 ± 0.31	85.07 ± 2.23	38.06 ± 0.13
P-value	*P < 0.001*	*P < 0.001*	*NS*

A significant difference on RR between all ambient temperature categories was observed ($P < 0.001$). The RR tended to increase among the THI increase ($y = 12.099 + 0.382$; $R^2 = 0.54$), as well as the HR ($y = 81.225 + 0.002$; $R^2 = 0.54$) and RT ($y = 37.894 + 0.007$; $R^2 = 0.56$), however, the environmental categories used in the present study were still under a range of thermoneutral conditions. Weather factors are closely correlated with RR reactions in cattle (Mader *et al.,* 2006). Zimbelman and Collier (2011) affirmed that the RR increases 2 breaths per minute (bpm) for each THI unit increase. Normally, the RR in cattle varies from 15–36 bpm, the HR from 60–80 beats per min and body temperature from 38.0–39.0 °C (Rosenberger, 1979, Jackson and Cockcroft, 2008). When the capacity for heat dissipation exceeds the range specified for normal activity, the body induces adjustments to avoid physiological dysfunction (Kadzere *et al.*, 2002). The present study confirmed that the respiration rate starts to increase earlier than the rectal temperature in hot conditions under rising air temperatures, which also has an advantage for visual measurements (Ferreira *et al.,* 2006, Moallem *et al.*, 2010).

Various factors such as body postures may influence the physiological parameters in cows. Our present study showed a significant effect of body posture on RR and HR of cows. Lying cows tended to show higher RR and HR in comparison with standing cows. Some works confirm that the individual cow factors can influence the physiological parameters and susceptibility of dairy cows to heat stress whereby the lying cows, for example, may develop heat stress earlier and at a lower temperature threshold than standing cows (Gaughan *et al.,* 2000, Berman, 2005). Some authors have suggested that the body contours of cows change when they lie down, causing the rumen compression on diaphragm and thereby affecting the thoracic organs, especially in the lung capacity and respiration effectiveness (Santos and Overton, 2001, Tucker *et al.,* 2008, Reece and Rowe, 2017). However, those cow factors were not included in the analysis of the normal physiological values, e.g. Rosenberger (1979) and Jackson and Cockcroft (2008), which can reduce the precise assessment of heat stress in cattle. Although in the literature has

been already mentioned that the straw bedding might increase the heat load in lying cows (Angrecka and Herbut, 2017); hence standing cows are more exposed to airflow and increase the wind convection (Wang *et al.,* 2018), no significant difference in cows' RT was observed in the present study.

New automatic RR sensor

The results of the correlation analysis showed a high correlation coefficient and coefficient of determination for the RR during lying ($r = 0.98$, $R^2 = 0.96$, $n = 15$) and standing ($r = 0.99$, $R^2 = 0.99$, $n = 20$) between automatic and visual counting. The sensor value appears to be the more reliable measure compared with the visual method due to the position of the sensor in the nasal cavity, where the pressure sensor really measures the inhalations and exhalations of the air into or out of the lung. The continuous measurement of RR in long-term studies is difficult to implement, can be physically strenuous, and inevitably results in miscounts. Nonspecific flank movements, which are not caused by respiration, can also result in misinterpretation (Eigenberg *et al.,* 2000). The new sensor enables animal-specific and high-frequency recording of respiration and characterisation according to frequency and depth. Furthermore, the permanent presence of a person can cause stress and affect the RR of the animal, which can confound the measurements.

Conclusions

In conclusion, the present study provides quantified evidence that the physiological parameters, especially RR, increase significantly with ambient temperature increase, even when the environmental conditions were still under thermoneutral conditions for dairy cows. Cows in a lying posture tended to demonstrate higher RR and HR than in a standing posture. The study also showed that measuring RR by a differential pressure sensor delivers reliable data. Overall, we found that the behaviour of the animals during the study was not disturbed by the flexible tube of the automatic sensor, nor was their health impaired.

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References

Angrecka, S. and Herbut, P. (2017). Eligibility of Lying Boxes at Different THI Levels in a Freestall Barn. *Annals of Animal Science,* 17: 257–269.

Berman, A. (2005). Estimates of heat stress relief needs for Holstein dairy cows. *Journal of Animal Science,* 83: 1377–1384.

Brown-Brandl, T.M., Eigenberg, R.A., Nienaber, J.A. and Hahn, G.L. (2005). Dynamic response indicators of heat stress in shaded and non-shaded feedlot cattle, Part 1: Analyses of indicators. *Biosystems Engineering,* 90: 451–462.

Costa, A.N., Feitosa, J.V., Junior, P.A., de Souza, P.T. and de Araujo, A.A. (2015a). Hormonal profiles, physiological parameters, and productive and reproductive performances of Girolando cows in the state of Ceara-Brazil. *International Journal Biometeorology,* 59: 231–236.

Costa, A.N., Feitosa, J.V., Montezuma, P.A., Jr., de Souza, P.T. and de Araujo, A.A. (2015b). Rectal temperatures, respiratory rates, production, and reproduction performances of crossbred Girolando

cows under heat stress in northeastern Brazil. *International Journal Biometeorology,* 59: 1647–1653.

Eigenberg, R.A., Hahn, G.L., Nienaber, J.A., Brown-Brandl, T.M. and Spiers, D.E. (2000). Development of a new respiration rate monitor for cattle. *Trans. ASAE.* 43: 723–728.

Ferreira, F., Pires, M.F.A., Martinez, M.L., Coelho, S.G., Carvalho, A.U., Ferreira, P.M., Facury Filho, E.J. and Campos, W.E. (2006). Parâmetros fisiológicos de bovinos cruzados submetidos ao estresse calórico. *Arquivo Brasileiro de Medicina Veterinaria e Zootecnia,* 58: 732–738.

Galán, E., Llonch, P., Villagrá, A., Levit, H., Pinto, S. and del Prado, A. (2018). A systematic review of non-productivity-related animal-based indicators of heat stress resilience in dairy cattle. *Plos One,* 13, e0206520.

Garner, J.B., Douglas, M., Williams, S.R.O., Wales, W.J., Marett, L.C., DiGiacomo K., Leury, B.J. and Hayes, B.J. (2017). Responses of dairy cows to short-term heat stress in controlled-climate chambers. *Animal Production Science,* 57: 1233–1241.

Gaughan, J.B., Holt, S.M., Hahn, G.L., Mader, T.L. and Eigenberg, R. (2000). Respiration rate - Is it a good measure of heat stress in cattle? *Asian-Australasian Journal of Animal Sciences,* 13: 329–332.

Hahn, G.L. (1999). Dynamic responses of cattle to thermal heat loads. *Journal of Animal Science,* 77(2): 10–20.

Jackson, P. and Cockcroft, P. (2008). Clinical Examination of Farm Animals. Wiley.

Kadzere, C.T., Murphy, M.R., Silanikove, N. and Maltz, E. (2002). Heat stress in lactating dairy cows: a review. *Livestock Production Science,* 77: 59–91.

Legates, J.E., Farthing, B.R., Casady, R.B. and Barrada, M.S. (1991). Body temperature and respiratory rate of lactating dairy cattle under field and chamber conditions. *Journal of Dairy Science,* 74: 2491–2500.

Mader, T.L., Davis, M.S. and Brown-Brandl, T. (2006). Environmental factors influencing heat stress in feedlot cattle. *Journal of Animal Science*, 84: 712–719.

Milan, H.F.M., Maia, A.S.C. and Gebremedhin, K.G. (2016). Technical note: Device for measuring respiration rate of cattle under field conditions1. *Journal of Animal Science*, 94: 5434–5438.

Moallem, U., Altmark, G., Lehrer, H. and Arieli, A. (2010). Performance of high-yielding dairy cows supplemented with fat or concentrate under hot and humid climates. *Journal of Dairy Science*, 93, 3192–3202.

Reece, W.O. and Rowe, E.W. (2017). Functional Anatomy and Physiology of Domestic Animals. Wiley-Blackwell, Hoboken, New Jersey, USA.

Rosenberger, G. (1979). Clinical Examination of Cattle. Parey, Berlin, Germany.

Santos, J.E.P. and Overton, M.W. (Year) of Conference. Diet, feeding practices and housing can reduce lameness in dairy cattle. In: *Intermountain Nutrition Conference*, Utah, USA., pp. 145–161.

Spiers, D.E., Spain, J.N., Sampson, J.D. and Rhoads, R.P. (2004). Use of physiological parameters to predict milk yield and feed intake in heat-stressed dairy cows. *Journal of Thermal Biology*, 29: 759–764.

Strutzke, S., Fiske, D., Hoffmann, G., Ammon, C., Heuwieser, W. and Amon, T. (2019). Technical note: Development of a noninvasive respiration rate sensor for cattle. *Journal of Dairy Science*, 102: 690–695.

Thom, E.C. (1959). The discomfort index. *Weatherwise*, 12: 57–61.

Tucker, C.B., Rogers, A.R. and Schutz, K.E. (2008). Effect of solar radiation on dairy cattle behaviour, use of shade and body temperature in a pasture-based system. *Applied Animal Behaviour Science*, 109: 141–154.

Wang, X.S., Zhang, G.Q. and Choi, C.Y. (2018). Effect of airflow speed and direction on convective heat transfer of standing and reclining cows. *Biosystems Engineering,* 167: 87–98.

West, J.W. (2003). Effects of heat-stress on production in dairy cattle. *Journal of Dairy Science*, 86: 2131–2144.

Zimbelman, R.B. and Collier, R.J. (Year) of Conference. Feeding Strategies for High-Producing Dairy Cows During Periods of Elevated Heat and Humidity. In: *Tri-State Dairy Nutrition Conference*, Fort Wayne, ID, pp. 111–125.

Session 10

Controlling Environment for Poultry Systems

RoboChick: An autonomous roving platform for data collection in poultry buildings, operational parameters and bird behaviour

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Abstract

Climate (temperature) control in poultry houses utilises standard environmental sensors in only a few locations, providing very crude indoor climate information. As a result provision of optimal conditions to all birds is difficult to assess and even more difficult to achieve. An autonomous roving sensor platform would be an ideal solution to provide these data at a high-density grid for the entire building. This feasibility study has clearly shown that a robot sensor platform can navigate through a flock of broilers during the majority of the growing cycle even on days with maximum stocking density. The 2dimensional environmental data collected for the building, clearly make the case for using the robot to assess the uniformity of the climate conditions at any location and time thus providing a real-time opportunity to improve the climate conditions experienced by the flock of broiler birds.

Keywords: real-time monitoring, autonomous robot, poultry, climate control

Introduction

Poultry meat is increasingly in high demand by consumers across the globe, far more than any other meat source. Worldwide, over 60 billion chickens are produced annually (FAOSTAT, 2015), whilst in the UK alone almost a billion broilers were slaughtered last year; and 60 million in Ireland (National Statistics, 2016). Food security and high welfare standards are key attributes that consumers associate with food quality. However, societal concerns over managing animal health and welfare in large poultry flocks are exacerbated by the threat of zoonotic disease caused by pathogens infecting poultry. These drivers place huge pressure on farmers to satisfy consumer demand for sustainable, safe, nutritious, affordable and animal welfare friendly products, while also reducing financial and health margins for error.

The modern broiler chicken is a product of intensive selection for fast growth and meat quality, requiring optimum conditions to perform to its genetic potential. Climate control, lighting, stocking density and litter quality are all important and interlinked parameters that must be maintained within narrow limits. Deviations from these optima can significantly impact on animal welfare, sustainability and profit. For example, localised deviations from the optimum temperature range are likely to result in a flock moving to the better maintained areas of the poultry shed (huddling), disrupting the normal feeding and drinking patterns, reducing weight gain and thus product yield (EFSA Panel on Animal Health and Welfare, 2012). Economies of scale and intensification have led to increasingly larger and better equipped farms, but also to a reduction in farmer time spent per animal, reducing the time spent observing broilers' performance, health status and behaviour. This increases the risk of producers missing food security and welfare issues at an early stage, increasing potential for significant financial loss and, in the case of disease and zoonoses, enhanced transmission within and between flocks and to humans.

Information and Computer Technology (ICT), combined with state-of-the-art monitoring can be used to address the trend of decreasing animal-farmer contact time by assisting

farmers in gathering information on their animals, processing and presenting the data in a user-friendly manner (Wathes *et al.,* 2008). This will improve not only broiler health and welfare, but can also provide an economic advantage to the farmer (Berckmans, 2013). Precision Livestock Farming (PLF) aims to continually monitor animals in confinement and analyse the data gathered to (i) provide information/alerts to the farmer and potentially, (ii) respond to the alert by actively changing relevant control parameters to alleviate the impact of the condition triggering the alert (added value). The poultry industry has adopted ICT and monitoring technology years ago, e.g. fully automated climate control, feeding and bird weighing systems and, although fully interactive growth control systems (Demmers *et al.,* 2011; Stacey *et al.,* 2004) are not yet implemented, adaptations from these (e.g. Flockman) are increasingly used in the broiler industry.

Currently the basic climate control in poultry houses utilises standard environmental sensors for temperature, relative humidity and carbon dioxide in only a few locations, providing rather rudimentary indoor climate data on which to base real time climate control. As a result, providing optimal conditions to all birds is difficult to assess and even more difficult to achieve. Precision livestock farming technologies such as eYeNamic, monitor bird behaviour, are increasingly used to mitigate the lack of data, but there is a distinct lack in climate data for the area around the birds themselves. An autonomous roving sensor platform would be an ideal solution to provide these data at a high-density grid for the entire building.

A recent exploratory study (Dennis *et al.,* submitted) showed it was feasible to operate a robot within a flock of broilers and has provided the operational parameters for an autonomous platform travelling through a broiler flock without causing negative bird behaviours, such as startling. Although many birds did come into contact with the front of the robot, and increasingly so with age and bird density, there were very few (17) instances during the crop where a bird refused or was unable to move out of the way of the robot. A standard protocol was used to move the robot around the bird obstructing its path. Standard production parameters (Food Conversion Ratio (FCR), mortality and growth rate) appeared to be unaffected by the use of the robot.

The thus developed robot platform was equipped with basic environmental sensors and a navigation system, based on previous applications of the robot platform, for instance, in the CERN large Hadron Collider in Geneva. The completed prototype robot was tested in a commercial broiler production facility to explore autonomous navigation and the collection of detailed spatially distributed environmental data. This paper will comment on the navigation and present the environmental data gathered.

Material and methods

Broiler production farm

The commercial feasibility trial with the autonomous robot, took place on a commercial broiler farm. Two identical houses were studied - one housed the experimental flock and one housed a control flock. The animals in both houses were matched for flock size, strain, age, stocking density and general husbandry. Both houses studied were 97.5 m × 23 m and had six full-length nipple drinker lines and four full-length pan feeder lines. The feeders and drinkers created 'aisles' that a stockman, and in the case of the experimental flock, a robot could travel down. The arrangement of furniture in the houses was identical. The floor was covered in a layer of sawdust prior to the arrival of the chicks and feed was scattered on blue paper throughout to encourage chicks to feed. Birds were fed *ad libitum*. The climate control was based on the Fancom MTT system using recommended temperature and humidity curves. The light regime provided a 2 h and a 6 h dark in any 24 h period. The EyeNamic system (six cameras) provided additional information on bird distribution and activity.

Animals

At one day old, 45,000 Ross 308 (Aviagen) broiler chicks were placed in both the experimental and control house (20 birds/m^2). The maximum stocking density was 38 kg/m^2. On Day 34, the birds were thinned to maintain the stocking density, removing 13,500 birds. The birds were depopulated at 40 days of age. The chicks in both houses arrived from the hatchery in poor health so were given antibiotics in the first week to recover. Additionally, both flocks suffered from bacterial enteritis at approximately 25 days of age and received an additional course of antibiotics. 'Play bales' (sawdust bales with the plastic covering split) were placed in the houses at 15 days of age.

A stockman walked both flocks three times a day for the first 16 days and twice a day for the remainder of the cycle. The stockman recorded all mortality (birds found dead and culls).

Robot platform

The autonomous robot (Figure 1) was based on the standard modular platform developed by Ross Robotics and fitted with a prototype cover. This cover was wedge shaped at the front to encourage birds to move sideways away from the robot as it approached and was high at the front to ensure birds could anticipate its arrival. Forward speed of the robot was 0.077 m.s^{-1} as recommended from a prior trial.

The robot was fitted with a lidar positioning system, optical target recognition system and wheel odometry for navigation purposes, video cameras for bird behavioural observations and a combined temperature, humidity and carbon dioxide sensor (CozIR, GSS ltd) and a sonic anemometer (Windmaster, Gill Ltd), both linked to a modular processing unit on the robot. The data were transferred in real-time to a dashboard and stored in a data base.

The anemometer was positioned horizontally at the rear of the robot to ensure airspeed was measured at bird level, whilst minimising the effect of the robot on the airflow pattern. The CozIR sensor was mounted on the top of the modular processing unit.

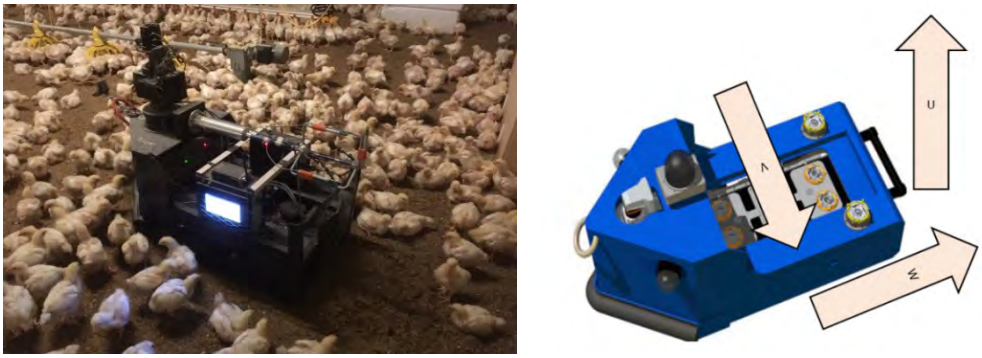


Figure 1. Prototype robot moving through flock with navigation stack including cameras at front, sonic anemometer and downward facing camera on pole presenting view of chickens directly in front of robot. The CozIR sensor is not visible. On the right a stylized image of the robot with the measurement axis of the sonic anemometer is shown

Experimental protocol

The robot was driven from the "hutch" along a set route (see Figure 2) twice a day Monday to Friday from Day 3 to Day 35. These runs were at approximately 10.00 and 13.30, with regular deviations due to technical difficulties with the robot.

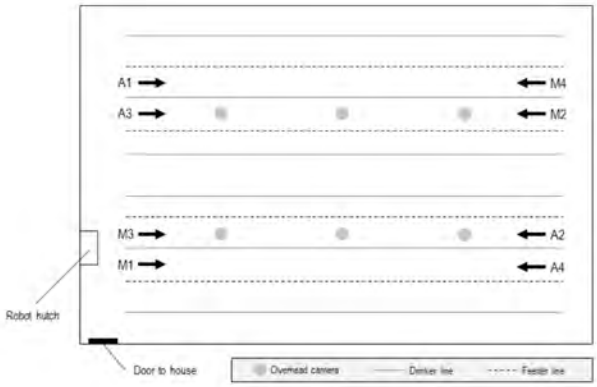


Figure 2. Layout of the experimental house. The route for a morning run is indicated by 'M' and the route for an afternoon route by 'A'. The dimensions of the house were 97.5 m × 23 m and the four aisles studied were 2.3 m wide

The robot was under manual control (operators outside of the room) at all times. Staff had to enter the room to power up the robot, open the hutch door and replace batteries only. Cameras on the robot were used to direct the robot and ensure that no birds were harmed. If a blocking bird was encountered the experimenter would pause the robot, and drive at the bird again. If the bird remained stationary, an attempt to go around it was usually initiated.

Results and discussion

The robot was tested from Day 3 to Day 35 of this crop of broilers. Unfortunately, technical difficulties with the navigation and remote control systems of the robot meant that the robot had to be controlled manually, initially from within the shed and from the second week remotely from the farm office. Location data generated by the navigation system were initially missing and following several hardware and software upgrades proved to be very accurate (± 0.010 m) but unstable, with the robot at times losing track of its position and unable to regain the correct location information, for instance, resulting in the robot thinking it was going in the opposite direction from reality or being over 50 m away. The working environment for the robot, e.g. 45,000 growing birds, variable litter conditions (uneven), large amount of objects and irregular features e.g. heaters was far more complex than anticipated and caused problems for particularly the Lidar system. The remaining time during the trial was insufficient to effect the major changes to either the existing hardware or introduce alternative location tracking systems.

Due to the problems with the navigation system, the number of environmental data sets with correct location information was limited. The temperature and relative humidity component of the CozIR sensor were heavily affected by the heat production of the environmental module itself and elements of the modular robot. Nevertheless, initial results using the temperature data from the anemometer do show the importance of spatial information.

The temperature profile as measured with the sonic anemometer for Day 35, Run 1 (am) is given in Figure 3. This clearly shows differences in temperature both by location and time. The deviation from the climate control sensors aiming to maintain 23.0 °C, exceeding 5 °C, was far greater than expected for a modern and well managed commercial building. There

were localised hotspots (up to 27.7 °C) at both ends of the building and cold spots (18.0 °C) near the staff entry door (used before the start and at the end of each run). The hotspots clearly indicate insufficient ventilation in these areas, whereas the cold spots could be due to staff entering the building, not only bringing in masses of cold air, but temporarily disturbing the airflow pattern due to the change in (under) pressure in the shed.

Equally, the airspeed measured (see Table 1 and Figures 4 & 5) clearly showed that the high speed inlet jet ventilation system works as expected on a well operated poultry building. The air is entering the building through air inlets in the sidewall, directed upward along the ceiling, then falling along the centre line of the building and finally, returning over the birds to either side wall having been warmed up in the process.

Table 1. The mean airflow as measured during the traverse of the robot over the length of the building along the V axis of the anemometer and the X axis of the building (U and V match on runs M1 and M3)

Pass	Mean airflow in V direction $m.s^{-1}$	Mean airflow in the X direction $m.s^{-1}$
M1	-0.3516	+ 0.3516
M2	-0.3253	-0.3253
M3	-0.3026	+0.3026
M4	-0.3662	-0.3662

On average, the airspeed along the V axis was 0.33 $m.s^{-1}$ which is within the comfort zone for broilers of this age (Charles, Scragg, & Binstead, 1981). The airspeed over the birds is higher towards the side walls (lane M1 and M4) as could be expected due to the airflow pattern generated by the high speed inlet jet system. The airspeed at the ends of the building appears slightly lower, however, this is well within the variation over time. The airspeed in the vertical plane (U) (Figure 4) measured in the lanes was low throughout as expected for a well operated inlet jet ventilation system. The centre lane of the shed, where a significant downward element of airspeed was expected could not be used due to obstruction by air re-circulation fans and "play" bales.

The hotspots in temperature appear to be coinciding with lower airspeed. Due to the building design (Tunnel inlets at one end of building, and partially obscured air inlets on the other end) might explain the findings to some extent, but this will need further investigation of the data before sound advice to ameliorate the issue can be given.

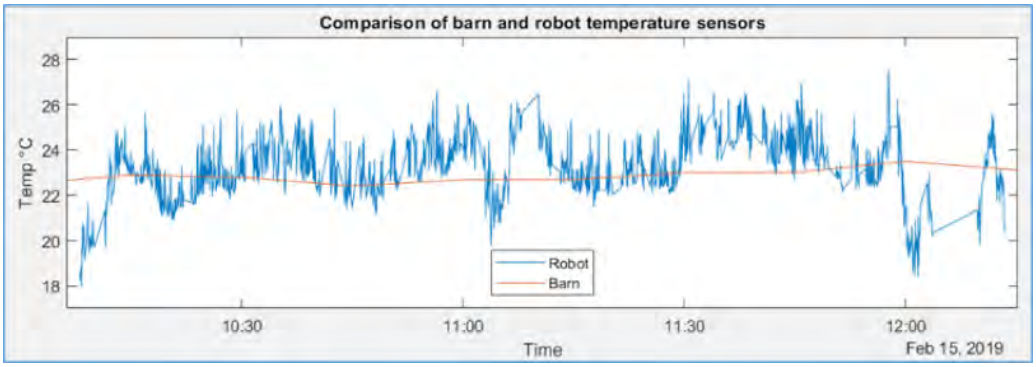
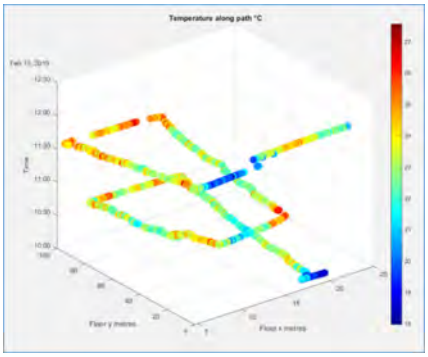


Figure 3. Temperature profile as measured with the sonic anemometer for the Day 35 Run 1 (am) in comparison to the equivalent temperature from the shed sensors (mean of four sensors) in the top graph and plotted against the robot location in the bottom graph



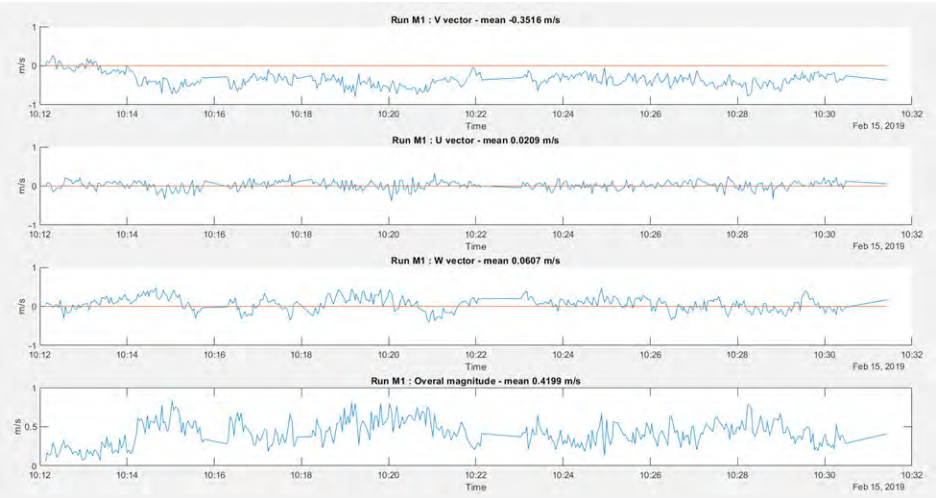


Figure 4. Airspeed profile (U,V and W vectors) as measured with the sonic anemometer mounted on the robot for the Day 35 Run 1 (am) over the length of the building for lane M1 only. Overall magnitude given for reference. Red line indicates 0 m.s^{-1}

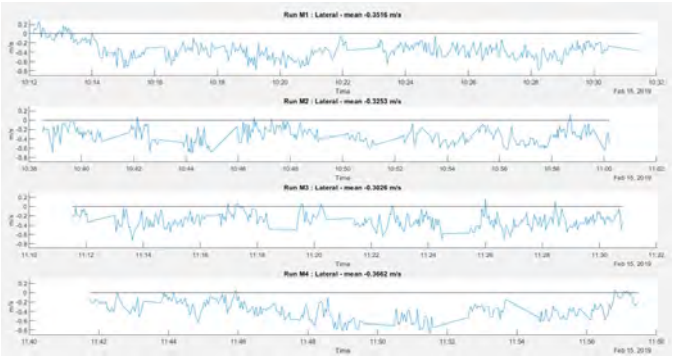


Figure 5. Airspeed profile for the lateral (V) vectors as measured with the sonic anemometer mounted on the robot for the Day 35 Run 1 (am) over the length of the building for lane M1 – M4. Black line indicates 0 $m.s^{-1}$

Conclusions

This feasibility study has clearly shown that a robot sensor platform can navigate through a flock of broilers during the majority of the growing cycle right up to days with maximum stocking density. However, the autonomous navigation system envisaged for the robot did not function properly. Further development and testing of the existing or a new navigation system is required.

The 2-dimensional environmental data collected for the building, clearly make the case for using the robot to assess the uniformity of the climate conditions at any location and time thus providing a real-time opportunity to improve the climate conditions experienced by the flock of broiler birds.

Acknowledgements

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References

Berckmans, D. (2013). Smart Farming for Europe; Value creation through Precision Livestock Farming. *Pan European Networks: Science & Technology,* 276–277.

Charles, D.R., Scragg, R.H., and Binstead, J.A. (1981). The Effects of Temperature on Broilers - Ventilation Rates for the Application of Temperature Control. *British Poultry Science, 22*(6): 493–498.

Demmers, T.G.M., Cao, Y., Gauss, S., Lowe, J.C., Parsons, D.J., and Wathes, C.M. (2011). Neural predictive control of broiler chicken growth. *British Poultry Abstracts, 7*(1): 17–18. doi:10.1080/17466202.2011.611619.

EFSA Panel on Animal Health and Welfare. (2012). Scientific opinion on the use of animal-based measures to assess welfare of broilers. *European Food Safety Authority Journal,* 10: 2774.

FAOSTAT. (2015). Retrieved from http://faostat3.fao.org/.

National Statistics. (2016). UK poultry slaughterings, weight and poultry meat production - montlhy dataset. *Latest poultry and poultry meat statistics.* Retrieved from https://www.gov.uk/government/statistics/poultry-and-poultry-meat-statistics.

Stacey, K.F., Parsons, D.J., Frost, A.R., Fisher, C., Filmer, D., and Fothergill, A. (2004). An automatic growth and nutrition control system for broiler production. *Biosystems Engineering,* 89(3): 363–371. doi:10.1016/j.biosystemseng.2004.07.006.

Wathes, C.M., Kristensen, H.H., Aerts, J.M., and Berckmans, D. (2008). Is precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall? *Computers and Electronics in Agriculture,* 64(1): 2–10. doi:10.1016/j.compag.2008.05.005.

Scratch the surface: histopathology of foot pad dermatitis in turkeys

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Abstract

The severity of foot pad dermatitis (FPD) is one important indicator for animal welfare in turkeys. Classification systems in Germany generally refer to a five-scale scoring (0-4). The aim of the present study was to describe interactions between visual scores and histopathological findings of the underlying pathology. Observer reliability was calculated for 600 feet of turkeys which were sampled at the slaughterhouse. Histopathology was conducted using 100 feet (20 feet per scoring scale). The size of the lesion was measured and feet were analysed histopathologically by examining the occurrence and severity grade of different parameters. Correlation between the visual score and the size of the lesion was strong (r_{sp} = 0.9). Apart from that, the presented study did not confirm a linear increase in the severity of the histological parameters with an increase of the severity in the visual score. Ulcerations were found in more than 50% of the feet visually scored as Level 1 already. For the visual scoring Levels 2-4, all of the feet were found to reveal ulcerations, most of the alterations being evaluated as severe. The presented study contributes to a better understanding of the pathophysiology of FPD. It also raises the question if, in view of animal welfare, threshold values of visual systems have to be adjusted considering the histopathological findings. However, further research on the perception of pain regarding ulcerations is needed.

Keywords: FPD, foot pad dermatitis, turkeys, histopathology, animal welfare

Introduction

Foot pad dermatitis (FPD), a contact dermatitis of the plantar surface of the bird`s feet (Greene *et al.*, 1985), is an important indicator of animal welfare in poultry husbandry. Besides other factors like genetics, nutrition and management (de Costa *et al.*, 2014; Shepherd and Fairchild, 2010), wet litter is reported to be the main reason to develop FPD (Mayne *et al.,* 2007; Mayne, 2005; Martland, 1984). Therefore, in Germany, the occurrence of FPD is evaluated at the slaughterhouse, among others, to draw retrospective conclusions about the management of litter and animal welfare during the period of husbandry.

The monitoring of such indirect animal welfare parameters can contribute significantly to the improvement of the management of farmed animals in the long-term, which first results from the incidence of FPD in broiler chickens in Denmark demonstrate. Here, since the introduction of an official monitoring in 2002, a massive decline in the prevalence of FPD was shown (Kyvsgaard *et al.*, 2013, de Jong and van Harn, 2012). In the case of foot pad assessment at the slaughterhouses in Germany, the scoring of FPD is established as a benchmark system, mainly to raise awareness among animal owners, and thus to progressively improve footpad health.

FPD is characterised by inflammatory processes and lesions of the skin. These can range from hyperkeratosis to necrotic alterations which might be affecting the surface and subjacent structures superficially (erosion) or deep (ulceration) (Greene *et al.*, 1985;

Martrenchar *et al.*, 2002). With regard to animal welfare, the occurrence of ulcerations is highly relevant, as ulceration is most likely to induce pain (Weber Wyneken *et al.*, 2015; Haslam *et al.*, 2007; Martland, 1984). Generally, the assessment of the severity of FPD is based on a subjective evaluation, scoring the area of the altered foot pad. The standard system used in turkeys was developed of Hocking *et al.* (2008); they propose to use a 5-step visual score based on the size of the colour-changed areas on the metatarsal pad.

Scoring systems have to fulfil a set of requirements: they must be quick and easy to use while reflecting the problem in measurable and assessable categories. Therefore, they must be clearly defined. As such systems also have to withstand economic competition - objectivity and validity are crucial additional criteria (Lund *et al.*, 2017, van Harn and de Jong, 2017). Therefore, repeatability between different classifiers should be an essential part of each scoring system. In Germany, some turkey slaughterhouses use automated setups to assess the severity of FPD in order to objectify such visual scoring systems as far as possible. The presented study is part of a collaborative project with the focus on optimising and validating one automated, camera-based device, most frequently used in Germany.

However, the presented study focuses on the visual scoring and does not draw conclusions to the automated system at this step. As mentioned above, one important criterion for a reliable scoring system would be to reflect the underlying problematic as precise as possible. Histopathological examinations can help to assess the severity of footpad changes in more detail (Michel *et al.*, 2012).

Therefore, the aim of the presented study was to describe interactions between visual scores and histopathological findings. The main focus was on the detection of ulcerations. In order to develop a basis to optimise automated camera-based detection of FPD, this study aimed to make a first step by analysing visually inaccessible pathologies and to reveal links between the superficial expression and their subjacent characteristics.

Material and methods

Observer Reliability

Observer reliability was calculated using 600 feet of turkeys (B.U.T 6) sampled at a slaughterhouse in Germany. Two hundred feet came from female birds while 400 feet belonged to male birds. Feet were randomly collected from the slaughterline and scored by two observers using a five scale scoring system adapted from Hocking *et al.* (2008). The definition of the different scoring classes can be found in Table 1.

Observer reliability was calculated using the "Prevalence-Adjusted Bias-Adjusted Kappa" (PABAK). Reliability was valued using the classification of Landis and Koch (1977) (PABAK<0.00 = poor; PABAK 0.00-0.20 = slight; PABAK 0.21-0.40 = fair; PABAK 0.41-0.60 = moderate; PABAK 0.61-0.8 = substantial; PABAK0.81-1.00 = almost perfect).

Table 1. Scoring classes of the visual scoring system (VS)

Scoring level	Definition
0	Intact foot
1	Small, punctual alterations
2	Altered lesion covers less than 25% of the foot pad
3	Altered lesion covers less than 50% of the foot pad
4	Altered lesion covers more than 50% of the foot pad

Table 2. Scoring classes of the combined histopathological score

Scoring level	Definition
0	Intact foot (including hyperkeratotic alterations)
1	Mild lesions (multifocal perivascular pododermatitis, erosions, re-epithelialized granulation tissue)
2	Slight ulcerations
3	Moderate ulcerations
4	Severe ulcerations

Histopathological Analysis

Feet of turkey toms were collected at the slaughter-line and scored visually (VS). Here again the scoring system described in Table 1 was used. Of those feet, 100 feet were picked in a pseudo-randomized order, with the criteria to include 20 feet per scoring class into the sample. These feet were used for further analysis.

To obtain the size, the lesion was measured by length × width, additionally the number of lesions was evaluated. Then, tissue was collected from the center of the biggest lesion/ per metatarsal foot pad. Cuts measured approximately 300 mm × 20 mm × 7 mm. They were stored in 10% buffered neutral formalin in histological cassettes and embedded into paraffin wax afterwards. Cross sections (3-4 µm thick) were stained using Haematoxylin/ Eosin. For microscopic examination, a light microscope (Olympus BX53) with 40 - 400x magnification was used. Histological analysis was performed by two experienced pathologists; examining the occurrence and severity grade (slight / moderate / severe) of different parameters. They included: hyperkeratosis, erosion, ulceration, re-epithelialized granulation tissue and multifocal perivascular pododermatitis. The latter was divided in acute and chronic processes according to the type of inflammatory cells; for the presented analysis both were pooled. The severity grade was evaluated semi-quantitatively. Multiple diagnoses were possible per foot. Furthermore, findings of the histopathology were combined in a single score (HS). This scoring was adapted to the scoring system proposed by Michel *et al.* (2012), however, it was modified slightly in order to allow better comparison to the VS (see Table 2). Spearman correlations were used.

Results and discussion

A PABAK of 0.72 was calculated. Taking the classification of Landis and Koch (1977) as a basis, this result can be considered to be a good reliability. We, therefore, concluded this visual scoring system to be an objective method for further usage throughout the study. However, both observers in this study were trained in scoring foot pad dermatitis. This has to be kept in mind when applying visual systems in practical contexts, visual scoring is vulnerable to a high subjective error, depending on the observer and the appropriate situation (Heitmann *et al.,* 2018, Meagher, 2009). Therefore, introducing automated devices seems to be a promising approach in order to standardise such assessment systems. However, besides being objective, repeatable and reliable (Hocking *et al.,* 2008), classification systems require a high degree of validity, this means they have to make sure that they reflect the problematic/disease as much as possible.

Therefore, the aim of the present study was to examine the underlying pathology in more detail, analysing feet of turkey toms histologically. The hypothesis of the study was that severity in the histological findings would increase with an increasing visual score.

Comparing the size of the lesions with the VS could confirm this assumption. Here, a high correlation (r_{sp} = 0.9) was calculated (Table 3). This was an expected result, as the VS bases on the size of the alteration. Furthermore, the results support the findings of the observer reliability, making the VS an objective method to reflect the spatial expression of the alteration.

Table 3. Spearmans' correlation coefficients between the VS and the analysed histopathological parameters

Parameter	Spearmans' correlation coefficient
Size of the lesion	0.90
Hyperkeratosis (occurrence / severity grade)	0.20 / 0.28
Multifocal perivascular pododermatitis (occurrence / severity grade)	0.25 / 0.31
Re-epithelialized granulation tissue (occurrence)	0.30
Ulceration (occurrence / severity grade)	0.75 / 0.81

However, there was no linear relationship of the remaining histopathological parameters according to the VS-level. Hyperkeratosis was found in all scoring classes. In VS 0-3, 100% of the feet were affected. In VS 4, 90% of the feet did show a hyperkeratosis, yet, the two feet, which were not diagnosed for hyperkeratosis, were found to have no intact epidermis left. The severity grade increased from VS 0 to VS 2 with a slight improvement in VS 3 and 4. Hyperkeratosis, described as thickening of the stratum corneum of the epidermis, resulting in a thickened layer of underdeveloped keratin, is discussed to be a permanent irritation of the epidermal surface in reaction to an external trauma (Shepherd and Fairchild, 2010). However, even if it may be regarded as pathological, with regard to animal welfare, this parameter is not supposed to be clinically relevant.

The multifocal perivascular pododermatitis was observed in 20% of the feet for VS 0 and in 40% for VS 1, revealing slight and moderate severity grades. In VS 2-4, the parameter was found for 55-75% of the feet, here revealing serious severity grades. Again, a slight improvement in VS 3 and 4 was noted. An improvement of such inflammatory processes with a rising severity of the VS seems not to be reasonable. Tissue was collected from the center of the biggest lesion. Especially for lesions of VS 3 and 4, the size of the necrotic area nearly covered all of the space available in the analysed cuts. We therefore discuss the 'improvement' to be due to the method with which the cuts were made, rather than to be due to an actual enhancement of the disease. The perivascular pododermatitis is defined by the occurrence of lymphocyte and heterophilic granulocytes around blood vessels, no loss of tissue is found at that stage. Therefore, these alterations are referred to as mild lesions (Shepherd and Fairchild, 2010).

Erosions as described in broilers (Greene *et al.*, 2008), were not detected in the presented study.

Re-epithelialized granulation tissue was observed for all VS-levels, with soring Levels 0 and 1 being affected with 20-35% and 60-65% in scoring Levels 2-4. Those findings imply old processes of healed, ulcerative pododermatitis. They, therefore, might not be relevant evaluating an acute disease incidence, nonetheless, in order to draw retrospective conclusions about the management of litter during the period of husbandry, it is considered to be a relevant factor.

All of those parameters might be classified as alterations with a minor clinical relevance (Greene *et al.*, 1985; Martrenchar *et al.,* 2002, Shepherd and Fairchild, 2010). Still, they give an interesting insight in the pathogenesis of FPD. Considering the linkage between VS and the histopathological findings, VS 0 feet should reveal none of the above mentioned parameters, VS 1 feet too, should be (at least) free of inflammation processes. In all of the analysed feet for the presented study, alterations were found for both VS-levels already.

However, in regard to animal welfare the occurrence of ulcerations is most interesting as they are often referred to as being painful (Weber Wyneken *et al.*, 2015; Haslam *et al.,* 2007; Martland, 1984), even if there is no clear evidence for this assumption yet. There are some studies referring to the gait and the activity of the birds (Hocking and Wu, 2013; Weber Wyneken *et al.*, 2015), drawing indirect conclusions to the painfulness of FPD. However, such studies are under discussion as other causes like femoral head necrosis (Dinev, 2009; Packialakshmi *et al.*, 2015) and osteomyelitis (Wyers *et al.*, 1991) are also quite common in fast growing poultry, both also resulting in gait difficulties. Still, until further evidence is produced, a prevention of ulcerations seems to be preferable in terms of animal welfare (Ekstrand *et al.,* 1997).

Ulcerations and VS revealed a high grade of correlation (0.75 / 0.81) (Table 3). A study by Heitmann *et al.* (2018) also found high correlation coefficients for ulcerations and the size of the lesion. Therefore, the VS might be a good indicator to implicate ulcerations generally. However, in our study ulcerations could be observed in VS 1 already. Here, 55% of feet were affected. In VS 2-4 all feet were affected. Most of those feet revealed severe ulcerations, no distinction could be made between VS-levels here. When assessing the severity of foot pad health, VS 1 and VS 2 generally are thought to play a minor role. Therefore, with regard to the ulcerations found in this study, the validity of the visual scoring system remains arguable.

The different parameters were combined in one scoring system (HS) following an approach which was established for broilers by Michel *et al.* (2012). Hyperkeratotic alterations were assigned to HS 0 in this study, given the fact that hyperkeratosis is not considered to be clinically relevant in terms of animal welfare and, due to the daily demand during the fattening period, histologically intact feet are delusive. HS 0 was found for 70% of the feet in VS 0. Still, 30% of the VS 0 feet were classified in HS-level 1, and therefore showing signs of mild alterations (granulation tissue / multifocal perivascular pododermatitis). In VS 1, 25% of the feet showed HS 2, 20% HS 3 and 15% HS 4, therefore over half of those feet were found to reveal ulcerative alterations. In VS 2-4 the majority of the feet were scored as HS 4 (80%, 95%, 90%) (Figure 1). With regard to the histological findings, these results indicate a substantial need to discuss the standard visual classification, especially when it is used as an indicator for animal welfare. However, studies concerning the pain level of above described alterations would be beneficial to clarify the relevance of the histopathological findings with regard to animal welfare.

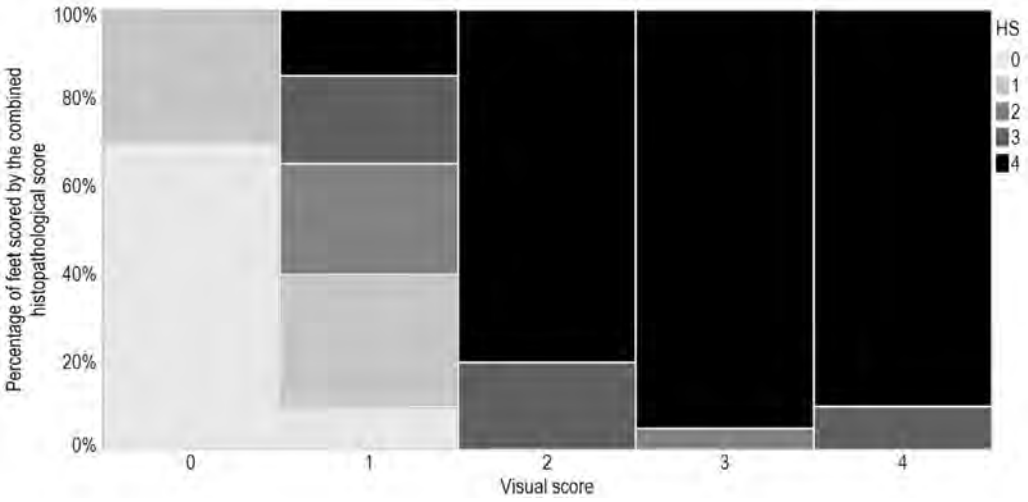

Figure 1. Percentage of feet (y-axis) scored by the combined histopathological score (HS 0-4, different grey scales from light grey to dark grey with rising severity) for the different visual scores (VS; x-axis)

Conclusions

To conclude, the presented results show that the visual score is reliable in representing the characteristic of the alteration regarding its dimension. In order to sensitise owners to the health status of their animals and to improve food pad health in a first step, the visual score might be sufficient. Using FPD as an indicator for animal welfare, the classification currently used, should be revised. Our findings suggest that small lesions as found in VS 1 and 2 are characterised by ulcerations already. Therefore, a refinement of the visual scoring system might be necessary until further research concerning the painfulness of those pathologies can resolve their role with regard to animal welfare.

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References

Da Costa, M.J., Grimes, J.L., Oviedo-Rondón, E.O., Barasch, I., Evans, C., Dalmagro, M. and Nixon, J. (2014). Footpad dermatitis severity on turkey flocks and correlations with locomotion, litter conditions, and body weight at market age. *Applied Poultry Research,* 23: 268–279.

De Jong, I. and van Harn, J. (2012). Management Tools to Reduce Footpad Dermatitis in Broilers. *Aviagen*, http://en.aviagen.com/assets/Tech_Center/Broiler_Breeder_Tech_Articles/English/AviaTech-FoodpadDermatitisSept2012.pdf.

Dinev, I. (2009). Clinical and morphological investigations on the prevalence of lameness associated with femoral head necrosis in broilers, *British Poultry Science,* 50: 284–290.

Ekstrand, C., Algers, B. and Svedberg, J. (1997). Rearing conditions and foot-pad dermatitis in Swedish broiler chickens. *Preventive Veterinary Medicine,* 31: 167–174.

Greene, J.A., McCracken, R.M. and Evans, R.T. (1985). A contact dermatitis of broilers—Clinical and pathological findings. *Avian Pathology,* 14: 23–38.

Heitmann, S., Stracke, J., Petersen, H., Spindler, B. and Kemper, N. (2018). First approach validating a scoring system for foot-pad dermatitis in broiler chickens developed for application in practice. *Preventive Veterinary Medicine,* 1: 154:63.

Kyvsgaard, N.C., Jensen, H.B., Ambrosen, T. and Toft, N. (2013). Temporal changes and risk factors for foot-pad dermatitis in Danish broilers. *Poultry Science* 92, 26–32.

Landis, J.R. and Koch, G.G. (1977). The Measurement of Observer Agreement for Categorical Data. *Biometrics,* 33: 159–174.

Lund, V.P., Nielsen, L.R., Oliveira, A.R.S. and Christensen, J.P. (2017). Evaluation of the Danish footpad lesion surveillance in conventional and organic broilers: Misclassification of scoring. *Poultry Science,* 96: 2018–2028.

Shepherd, E.M. and Fairchild, B.D. (2010). Footpad dermatitis in poultry. *Poultry Science,* 89: 2043–2051.

Martrenchar, A., Boilletot, E., Huonnic, D. and Pol, F. (2002). Risk factors for foot-pad dermatitis in chicken and turkey broilers in France. *Preventive Veterinary Medicine,* 52: 213–226.

Mayne, R.K. (2005). A review of the aetiology and possible causative factors of footpad dermatitis in growing turkeys and broilers. *World's Poultry Science Journal,* 61: 256–267.

Martland, M.F. (1984). Wet litter as a cause of plantar pododermatitis, leading to foot ulceration and lameness in fattening turkeys. *Avian Pathology*, 13: 241–252.

Mayne, R.K., Else, R.W. and Hocking, P.M. (2007). High litter moisture alone is sufficient to cause footpad dermatitis in growing turkeys. *British Poultry Science* 48: 538–545.

Meagher, R.K. (2009). Observer ratings: validity and value as a tool for animal welfare research. *Applied Animal Behaviour Science,* 119, 1–14.

Michel, V., Prampart, E., Mirabito, L., Allain, V., Arnould, C., Huonnic, D., Le Bouquin, S. and Albaric, O. (2012). Histologically-validated footpad dermatitis scoring system for use in chicken processing plants. *British Poultry Science,* 53: 275–281.

Haslam, S.M., Knowles, T.G., Brown, S.N., Wilkins, L.J., Kestin, S.C., Warriss, P.D. and Nicol, C.J. (2007). Factors affecting the prevalence of foot pad dermatitis, hock burn and breast burn in broiler chicken. *British Poultry Science,* 48: 264–275.

Hocking, P.M. and Wu, K. (2013). Traditional and commercial turkeys show similar susceptibility to foot pad dermatitis and behavioural evidence of pain. *British Poultry Science,* 54: 281–288.

Hocking, P.M., Mayne, R.K., Else, R.W., French, N.A. and Gatcliffe, J. (2008). Standard European footpad dermatitis scoring system for use in turkey processing plants. *World Poultry Science Journal,* 64: 323–328.

Packialakshmi, B., Rath, N.C., Huff, W.E. and Huff, G.E. (2015). Poultry Femoral Head Separation and Necrosis: A Review. *Avian Diseases,* 59: 349–354.

Van Harn, J. and de Jong, I. (2017). Validation of Meyn Footpad Inspection System. *Wageningen Livestock Research Report* 1044 B.

Wyers, M., Cherel, Y. and Plassiart, G. (1991). Late Clinical Expression of Lameness Related to Associated Osteomyelitis and Tibial Dyschondroplasia in Male Breeding Turkeys. *Avian Diseases,* 35: 408–414.

Weber Wyneken, C., Sinclair, A., Veldkamp, T., Vinco, L.J. and Hocking, P.M (2015). Footpad dermatitis and pain assessment in turkey poults using analgesia and objective gait analysis. *British Poultry Science,* 56: 522–530.

Developing a machine vision system for detecting laying hens

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Abstract

The Israeli laying hens industry is regulated by quota; a farm can produce eggs according to a fixed number of hens. With the new community cages now integrated into the Israeli egg industry, a manual head count of the hens is an impossible task. The aim of this study is to develop a machine vision system that automatically counts the hens, and helps the regulator to control the industry. The hen house that was used is 87 m long stacked on six floors, with 37 community cages set in a row, each cage is 2.4 m long, 0.54 m tall, and 0.74 m depth, housing 18–34 hens. The hen house has a narrow path along the cages. Consequently, a wide-angle camera was applied (HD Action Camera 1080p, wide angle 170 deg' lens) in order to frame the entire cage in a single field of view. The camera was mounted on a steel arm 0.85 m from the cages. The arm was connected to the feeder that moves along the cages. Videos with 30 fps were processed with an AI detection algorithm called Faster R-CNN. A feeding event appeared to be an adequate time to count the hens, as all hens were lined up in front of the cage, visible to the camera, making it possible to count. The detection algorithm was trained to detect hens in cages; it was tested on 4,000 images and got an accuracy of 80%. The algorithm count was compared to human observer count used as ground truth. The accuracy can be improved by further training the algorithm parameters.

Keyword: object detection, deep learning, Faster R-CNN, laying hens

Introduction

Machine vision is widely used in the poultry industry, with a variety of applications such as birds clustering monitoring (Zaninelli *et al.*, 2018), weight estimation, and limp (Aydin, 2017) and other injury detection. The above examples were developed for litter floor houses (not for battery cages), therefore the camera angle and distance from the bird is not a limitation.

Community cages are long structures with narrow paths along them, constraining the camera maximum distance. The camera angle was also limited because some of the hens lined up in front of the cage, and some stood at the back; thus, in order to capture them all in one frame, the camera was well-adjusted.

Another problem was the hens' sensitivity to the presence of a new object in their surroundings. The presence of the camera mounted on a rod was identified as a foreign object by them and it elevated their stress level and irritation, thus affecting counting success.

To address the above difficulties, a wide angle camera was used, and the Faster R-CNN detection algorithm was employed. The algorithm can detect multiple objects in an image. The algorithm was tested on images taken under those constricting conditions of dense objects (hens) and challenging angle and illumination conditions. In this work the chicken behaviour was monitored, to detect when they are in the best position for counting. The chickens were recorded with minimum disturbance in their habitat. The research is aiming to lay the foundations for an apparatus that can be installed in hen houses containing community battery cages, and count the hens. It can help the caretaker, but also a regulator to control the industry, ensure the poultry welfare including the five freedoms, and increase the eggs' quality.

Materials and methods

Camera setup

The camera used in this research is an off the shelf product -A Media Tech W9R with a 170 deg' wide angle lens. The camera was tuned to full HD mode (1080p), filming 30 frames per second (fps). The hens in this research were recorded while the camera was mounted on a steel rod attached to the feeder, 90 cm in front of the cages, and positioned in a way that allowed direct view of the hens (Figure 1). The reason the camera was positioned in such an angle was due to the structure of the community hen house that allowed front view access only. The maximum distance from the cages is restricted to 90 cm, based on the narrow path besides them. An image taken using this setup can be seen in Figure 3.

(a) (b)

Figure 1. Camera setup (a) The whole width of a cage (marked in black) is enclosed in the camera field of view; (b) The camera was positioned 90 cm from the front of the cages

Hen house experiment

The system was examined in one hen house 87 m long, on the second floor that contains 37 cages, each cage is 2.4 m long, 0.54 m tall, and 0.74 m depth, housing 18–34 hens per cage.

Figure 2. The test battery cages hen house, with an arrow pointing to the second floor that was recorded

Observation

In order to find the optimal time for counting, a few observations were made. The behaviour of the hens was monitored in order to understand their habits. Feeding events occur four times a day, at 6:30, 13:30, 14:30, and 17:00. Following the feeding routine up to 15:00, most of the hens sat in the cages and laid eggs; sitting at the back of the cages and huddling together, reduced our ability to count them. The last feeding event was selected as the adequate time point for counting, as most hens stood in front of the cages and waited for the last meal of the day.

Data collection

Hens are easily frightened by any foreign object such as a person's presence or a camera sticking out from the feeder. In order to accustom the hens to the presence of the camera, a dummy camera was installed on the feeder three days prior to data collection.

Following the adaptation period, the hens were video-recorded for 30 minutes during the last feeding event of the day. The recording was made with minimum disturbance, automatically, with no human presence. During the feeding event, the feeder travelled back and forward, so every cage was recorded twice. Frames that contained a whole cage (about 60 frames per feeder traveling down a single cage) were saved, in total 120 frames per cage were obtained, at a camera speed of 30 fps.

Object detection algorithm

Faster R-CNN is an object detection algorithm based on deep convolutional network (Ren *et al.*, 2017). It belongs to a deep learning object detection family called Region Based Detectors (RBD). RBD methods comprise two modules – a Region Proposal Network (RPN) and a classifier. The RPN is an attention mechanism, which tells the classifier where to look for an object in the image. It takes about a second to process an image with Faster R-CNN.

In the Faster R-CNN method, the RPN detects regions in an image with high probability to have objects in them. First the image is fed into a pre-trained base model, then the RPN slides on top of the last convolution layer and finds 300 regions in the original image with high probability to have objects in them.

After the region proposals process, the proposed regions are fed into the second module of the Faster R-CNN, which classifies and corrects the bounding boxes' locations. The output of this process is an image with bounding boxes around the objects it has found.

Figure 3. Hens detected by the algorithm. The whole width of the cell is enclosed within the frame

Implementation details

In order to train the Faster R-CNN algorithm, a dataset containing 359 labeled images was created. The base model used was ResNet101 pre-trained on "coco" dataset, a labeled object detection dataset. The training was done on a dataset containing 359 labeled images, divided into 287 train images and 72 validation images. A labeled image contains an 'xml' file with the ground truth boxes' coordinates. The number of chickens in every cage was counted by a human observer, and used as a ground truth number.

Object detection algorithm performance

In order to measure the performance of an object detection algorithm, one should examine Recall and Precision. Recall is the proportion of TP out of the possible positive examples in the ground truth ($Recall = \frac{TP}{TP+FN}$). Precision is the proportion of TP out of the positive results given by the algorithm ($Precision = \frac{TP}{TP+FP}$)

Recall is a measure of the algorithm's ability to find all the positive examples. Recall close to one will yield low Precision, because all the detected objects will be classified as chickens. Precision close to one will introduce a low Recall, because all the detected

objects classified as chicken are true, but not all the chickens in the image are found.

In order to construct the Precision–Recall curve, the model score threshold should be changed (if score >threshold,the object is a chicken) in the range of 0–1. The area under this graph is called the Mean Average Precision (mAP), and it is the performance measure for an object detection algorithm.

A classification is true if it matches the ground truth with IoU > N, where IoU is the intersection over union between the predicted and the ground truth bounding boxes, defined as, $IoU = \frac{area\ of\ overlap}{area\ of\ union}$, 0<IoU<1. IoU is a way to measure if a predicted bounding box is well-located; high IoU means that a predicted bounding box has a big overlap with a ground truth bounding box. N is a number between 0–1, and it is a threshold for IoU.

Results and discussion

Table 1 shows the results of the validation set with 72 labeled images. The second and third columns shows the result of mAP for N = 0.50 and 0.75.

When IoU = 0.50 the results are good, the required overlap between the ground truth boxes and the predicted boxes is low. Most of the results found with this IoU are correct, and most of the chickens were detected. For IoU = 0.75 the mAP has dropped, because the overlap required for a true prediction is high. The drop in the mAP suggests that a lot of the detections are made in the range of 0.5 < IoU < 0.75.

Table 1. mPA with different IoUs

IoU	0.50	0.75
mPA	0.961	0.358

Average Recall (AR) is the maximum recall, given a fixed number of objects detected per image. AR is averaged over all IoUs and categories (in this work there is only one category - 'chicken'), in the range of 0.5–0.95 with jumps of 0.05.

Table 2. AR with different number of objects

Number of objects	1	10	100
AR	0.027	0.268	0.557

AR increases when more objects are detected, because when more objects are classified as chicken, the TP results are most likely to increase.

Average precision (AP) presented in Table 3 is averaged over all the IoUs, and relates to different object size; {*small:area <322 pixies*}, {*medium:* $32^2 < area < 96^2$}, {*large:* $area < 96^2$}.

Table 3. AP with different size of objects

Area	small	medium	large
AP	0.200	0.472	0.482

Table 4. Maximum detected chicken in every cell

Cage number	Forward max	Backward max	Gold standard reference
1		27	29
2	28	28	28
3	26	26	28
4	30	27	31
5	24	22	26
6	25	26	29
7	24	25	28
8	26	25	28
9	21	20	27
10	20	22	23
11	23	21	27
12	25	22	28
13	27	29	30
14	24	24	29
15	28	25	32
16	22	22	25
17	27	24	28
18	27	27	29
19	30	24	32
20	27	29	32
21	31	30	34
22	21	22	25
23	23	24	28
24	27	21	26
25	21	22	24
26	26	23	27
27	23	22	24
28	22	21	23
29	21	18	22
30	18	17	19
31	21	19	23
32	24	16	25
33	22	22	24
34	18	21	21
35	15	16	18
36	18		23
37	18		22

AP is increasing with object size, chicken areas in the images are bigger than the small area mentioned in Table 3.

Table 4 presents the maximum count for each cage. The maximum values were chosen out of 60 frames, from the back and forth movement of the feeder.

On the way forth 853 chickens were detected, and 809 on the way back; this is 90% and 86.8% of the total number in the ground truth. These results were calculated with a certainty level of 0.8 and IoU > 0.6.

Conclusions

With Faster R-CNN algorithm, counting laying hens in battery cages can be done with up to 90% accuracy. The algorithm can detect objects in a densely populated picture, containing multiple overlapping objects.

With more training images from different cages, more hens can be detected.

Further work is still needed in order to increase accuracy, including adding more information from the scene to the training process, such as stereo images.

References

Aydin, A. (2017). Development of an early detection system for lameness of broilers using computer vision. *Computers and Electronics in Agriculture,* 136: 140–146.

Girshick, R. (2015). Fast r-cnn. In *The IEEE International Conference on Computer Vision*. ICCV '15 Proceedings of the 2015 IEEE International Conference on Computer Vision (ICCV), IEEE Computer Society, Washington, DC, USA, pp. 1440–1448.

Girshick, R., Donahue, J., Darrell, T., & Malik, J. (2014). Rich feature hierarchies for accurate object detection and semantic segmentation. In *The IEEE Conference on Computer Vision and Pattern Recognition*. CVPR '14 Proceedings of the 2014 IEEE Conference on Computer Vision and Pattern Recognition, IEEE Computer Society, Washington, DC, USA, pp. 580–587.

Kashiha, M.A., Green, A.R., Sales, T.G., Bahr, C., Berckmans, D., & Gates, R.S. (2014). Performance of an image analysis processing system for hen tracking in an environmental preference chamber. *Poultry Science*, 93: 2439–2448.

Ren, S., He, K., Girshick, R., & Sun, J. (2017). Faster R-CNN: towards real-time object detection with region proposal networks. *IEEE Transactions on Pattern Analysis & Machine Intelligence*, 6: 1137–1149.

Uijlings, J.R., Van De Sande, K.E., Gevers, T., & Smeulders, A.W. (2013). Selective search for object recognition. *International Journal of Computer Vision*, 104: 154–171.

Wang, C., Chen, H., Zhang, X., & Meng, C. (2016). Evaluation of a laying-hen tracking algorithm based on a hybrid support vector machine. *Journal of Animal Science and Biotechnology*, 7: 60.

Zaninelli, M., Redaelli, V., Luzi, F., Mitchell, M., Bontempo, V., Cattaneo, D., ... & Savoini, G. (2018). Development of a Machine Vision Method for the Monitoring of Laying Hens and Detection of Multiple Nest Occupations. *Sensors*, 18: 132.

Zhuang, X., Bi, M., Guo, J., Wu, S., & Zhang, T. (2018). Development of an early warning algorithm to detect sick broilers. *Computers and Electronics in Agriculture*, 144: 102–113.

Effects of ammonia concentration on production parameters and blood profiles of laying hens exposed to a chronic heat stress

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Abstract

Few evidence is available currently to reveal the effect of long period ammonia on the immune function and productivity of laying hens when simultaneously exposed to a chronic heat stress. The present study was conducted to determine the adverse effects of ammonia concentration on egg productivity, egg quality, and immune function in commercial laying hens. A total of 240 × 17-wk-old Hyline Brown laying hens were randomly distributed into three treatments, including the CON (ammonia concentration of 0-5ppm), the low ammonia group (ammonia concentration of 20ppm), and the high ammonia group (ammonia concentration of 45ppm). Meanwhile, all birds were housed in cages (two birds per cage) and received the ammonia pollution when exposed to a chronic heat stress (34-35 °C) for 20 weeks in three artificial environmental chambers. Different samples of production and immune parameters were collected and measured in the present study. As results, high ammonia concentration significantly influenced body weight, egg weight, feed intake and egg production of the birds. In addition, the levels of plasma T-AOC in low and high ammonia groups were significantly lower than the control group. Excessive ammonia led to the significantly decreased levels of plasma luteinizing hormone ($P < 0.05$), IgG ($P < 0.05$), and increased plasma corticosterone levels ($P < 0.05$) with no evident regularity. Our results suggest that excessive ammonia along with high temperature can serve as a physiological stress factor and has negative effects on production performance and immune function.

Keywords: production parameters, ammonia, heat stress, blood profiles, immunity, laying hens

Introduction

Aerial ammonia is a colourless gas with a strong pungent smell, which is recognised as one of the most noxious odours in poultry operations, and its negative effect on environment has been documented by numerous studies (Koerkamp, 1994; Koerkamp *et al.*, 1998; Wheeler *et al.*, 2000). Poultry production industry, as the largest contributor to ammonia emissions of all animal husbandry operations, has undergone considerable surveillance from public and regulatory agencies due to their environmental impacts (Lin *et al.*, 2017). Meanwhile, poultry companies have to be concerned not only for worker health, but also for poultry health because elevated concentrations of atmospheric ammonia has adverse impact on bird physiology and productivity (Carlile, 1984). Ammonia is known as an irritant alkaline air contaminant, with occupational limits set by OSHA (Occupational Safety and Health Administration) at 50 ppm for the 8 h permissible exposure limit, and immediately dangerous to human life and health level is considered to be 300 ppm (Wheeler *et al.*, 2000).

Amounts of studies have been carried out to indicate the significant influences on health and growth performance of poultry exposing to ammonia, most of which focus on broilers. Excessive ammonia is a physiological stress factors that will reduce feed intake and stunt growth (Beker *et al.*, 2004; Charles & Payne, 1966; Deaton *et al.*, 1984; Wei *et al.*, 2014),

decrease egg production significantly 7 weeks' exposure to ammonia at the ammonia concentration of 102ppm (Charles & Payne, 1966) and increase the incidence of diseases and secondary infections such as Newcastle disease, airsacculitis and prevalence of Mycoplasma gallisepticum (Anderson *et al.*, 1964; Oyetunde *et al.*, 1978; Sato *et al.*, 1973).

The undigested nitrogenous substance in poultry manure such as protein, amino acids, and microbial nitrogen are quickly decomposed into gaseous ammonia by microorganism and distributed to surrounding air under proper temperature and humidity condition (Koerkamp & Bleijenberg, 1998; Xin *et al.*, 2011; L. Zhao *et al.*, 2016). The commonly recommended indoor ammonia level for poultry house in China has been limited to 15 mg/m^3 (20 ppm). With the development of mechanization and automation, the air environment in poultry house has been greatly improved due to the mechanically ventilation technology. However, many poultry farms in China still have poor air condition and elevated ammonia concentration resulting from poor ventilation, inadequate manure handling schemes, excessive bird density, especially in high temperature season (Xin *et al.*, 2011; Y. Zhao *et al.*, 2013). As is well known, laying hens live longer than broiler chickens in poultry house and may develop a variety of disorders suffering from extended period of ammonia exposure (Beker *et al.*, 2004). Despite a multitude of research on the adverse effects of ammonia on the health and performance of poultry, few evidence is available currently to reveal whether the immune system and productivity of laying hens .change under long periods of ammonia exposure in hot climate. Therefore, the objective of this work was carried out to evaluate the effects of ammonia on the immune system and productivity under high temperature.

Materials and methods

Materials and experimental conditions

Three artificial environmental chambers (each 24.8 m^2, 4.5 × 5.5 m) were built for the experiment. Cages (50 × 40 × 40cm, L × W × H) were set evenly on opposite sides of the chamber for hens breeding. The chambers were computer programmed to keep the environmental factors as required. Sensors installed in these chambers delivered signals of temperature, humidity, ammonia and carbon dioxide concentration every 10 s, then displayed on the computer screen for observation.

The supply system of ammonia gas was detailed by researchers (Jones *et al.*, 1997) in order to maintain the desired ammonia concentrations. Compressed anhydrous ammonia was stored in a cylinder of and its flow rate was adjusted by a flow meter. This design enabled each chamber to be filled with gaseous ammonia independently of the other ones.

LED lamps (5-300lx) were placed on the ceiling of the chamber respectively, which could adjust the light intensity by using luminometer. Temperature was adjusted automatically by air conditioner and air inlet and outlet were trepanned for mechanical ventilation. Feeder and drinker were provided in each chamber and video cameras were fitted.

Bird management and experimental design

A total of 240 Hy-Line Brown hens acquired from a commercial pullet grower farm were used for this study. Birds were transferred to the cages (two birds per cage) for two weeks acclimation at the age of 17 weeks before the ammonia pollution. Meanwhile, based on a single factor experimental design, birds were randomly assigned to three groups with eight replications and 10 birds per replicate, including three treatments of ammonia concentration exposure: 0-5ppm (the control group, CON), 20ppm and 45ppm. All birds were provided with a corn-soybean basal diet and feed and water was provided *ad libitum*. The ambient temperature and relative humidity (RH) were respectively kept at 34 - 35 °C and 40 - 60%, carbon dioxide level was kept below 1,000ppm during the experimental period.

For light treatment, during the growing period from 17 wk up to 38 wk, the light regimen was 11 h (4.00 – 15.00) every day for hens in the first week and then stepped up gradually per week until it reached 16 h (4.00 – 20.00) in 31 wk. From then on, it turned to permanent illumination of 16 h from 32–38 wk. Besides, light intensity of 30 lx was equalised at bird head level following the HyLine Brown Layers Guide Manual (Hy-Line International. http://www.hyline.com).

Sample preparation and collection

Feed consumption, egg production per replication was recorded weekly and all eggs were weighed on 1 d/wk. Meanwhile, for each treatment, 32 eggs (four egg/ replication) were collected randomly for egg weight test. For each sampling, two birds were randomly selected from each replicate and weighed for individual body weight (BW) every week after fasting for 12 h starting at wk 18, then wing venipuncture was performed for blood and sera were prepared after centrifuging. All eggs were stored at 4 °C and sera samples were stored at -20 °C .

Measured contents and methods

The concentrations of blood parameters were detected by Enzyme Linked Immunosorbent Assay (ELISA, kits purchased from Jianglai Biological Technology Co. Ltd., Shanghai, China). Sample (50μl) was added in each well after standard substance was diluted. The following operation was to dilute the sample (50μl) five times before adding in the wells and incubate at 37 °C for 30 minutes. Washing liquid was added to the waste liquid hole for 30 seconds, repeatedly for five times. Then, ELISA reagents (50μl) were added in each well, and developers A and B (each 50μl) were added and incubated at 37 °C for 15 minutes. Lastly, stop buffer (50μl) was added to terminate the reaction (blue turned to yellow). Absorbance values were measured at 450 nm, and results were analysed.

Statistical analysis

All data were analysed by 1-way ANOVA with SPSS 23.0 software, according to the design of the 2 experimental groups (20ppm, 45ppm) and 1 control group (0-5ppm). Differences among groups were determined using Duncan's multiple range test and considered to be significant at $P < 0.05$.

Results and discussion

Effect of ammonia and high temperature on production parameters of laying hens

During the experimental period, egg production and feed intake of the three treatments rise first and descended later, the top of egg production of the treatments were, respectively, 95.29% (CON, 31-34 wk), 88.16% (20ppm, 27-30 wk) and 84.52% (45 ppm, 27-30 wk). The daily feed intake went to the top at 27 – 30 wk and they were respectively, 126.21 g (CON), 116.27 g (20ppm) and 113.15 g (45ppm).The body weight of the birds in all treatments increased with time and body weight of CON was greater than the other two treatments in every experimental period. The EW of the hens increased with age (Table 1).

At 19 - 22 wk, DFI of hens in CON was significantly greater than that of hens in others ($P < 0.001$) until 35 – 38 wk. At 23 – 26 wk, 27 – 30 wk, 31 – 34 wk and 35 – 38 wk, hens in CON showed higher EP than others ($P<0.001$). In every period of the experiment, EW of the CON were heavier than the two treatments exposed to ammonia and it presented significant difference from 23 - 26 wk ($P = 0.048$).

Excessive ammonia led to a decrease of poultry production, including daily feed intake, egg production, body weight and egg weight compared with a clear atmospheric environment according to our study. Ammonia is a physiological stress factors that reduced feed intake

and stunt growth (Beker *et al.*, 2004; Charles & Payne, 1966; Deaton *et al.*, 1984; Wei *et al.*, 2014), our study verified this statement. It decreased egg production significantly under 12 weeks' exposure to ammonia at the ammonia concentration of 20 ppm and 45 ppm, which was close to the conclusion of Charles (Charles & Payne, 1966).

Table 1. The main effects of ammonia concentration on production parameters exposed to a chronic heat stress

	Items[1]	Treatment			SEM	P value
		0-5ppm	20ppm	45ppm		
19-22wk	DFI, g	104.02[a]	98.36[b]	89.31[c]	1.290	<0.001
	EP, %	40.67	37.50	31.33	0.023	0.234
	BW, g	1,644.29	1,627.38	1,624.58	15.826	0.863
	EW, g	48.95	47.97	48.07	0.392	0.540
23-26wk	DFI, g	112.35[a]	100.89[b]	103.43[b]	1.319	<0.001
	EP, %	86.64[a]	78.70[b]	75.20[b]	0.012	<0.001
	BW, g	1,709.54[a]	1,693.17[a]	1,626.88[b]	13.157	0.023
	EW, g	53.19[a]	52.88[ab]	52.48[b]	0.133	0.048
27-30wk	DFI, g	126.21[a]	116.27[b]	113.15[b]	1.231	<0.001
	EP, %	90.08[a]	88.16[a]	84.52[b]	0.007	0.003
	BW, g	1,761.83[a]	1,743.00[a]	1,672.04[b]	13.649	0.016
	EW, g	57.07[a]	56.72[a]	53.45[b]	0.146	<0.001
31-34wk	DFI, g	116.77[a]	94.60[b]	91.71[b]	2.220	<0.001
	EP, %	95.29[a]	80.60[b]	76.83[c]	0.089	<0.001
	BW, g	1,813.33[a]	1,764.33[ab]	1,710.04[b]	14.060	0.009
	EW, g	59.21[a]	57.28[b]	53.06[c]	0.414	<0.001
35-38wk	DFI, g	115.04[a]	90.89[b]	77.17[c]	2.741	<0.001
	EP, %	94.54[a]	74.60[b]	72.94[b]	0.084	<0.001
	BW, g	1,812.75	1,757.92	1,748.17	23.681	0.5
	EW, g	60.76[a]	59.23[a]	50.59[b]	0.458	<0.001

a,b,c Values with different letters in the same row indicate significant difference ($P < 0.05$).
[1]DFI means the daily feed intake, EP means the egg production, BW means the body weight, EW means the egg weight

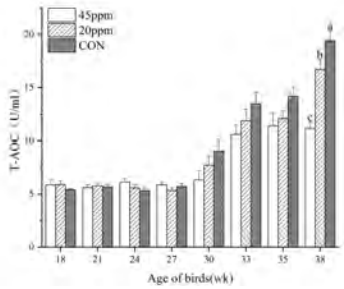

Figure 1. Blood T-AOC of hens

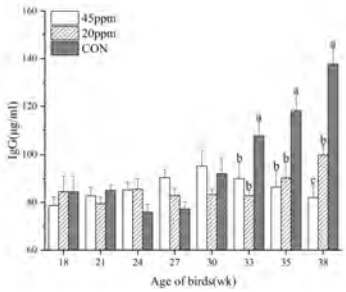

Figure 2. Blood IgG concentration of hens

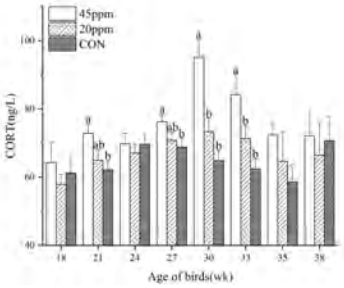

Figure 3. Blood CORT level of hens

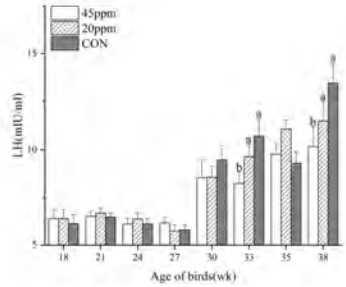

Figure 4. Blood LH concentration of hens

The blood total antioxidant capacities (T-AOC) and blood IgG concentrations of the laying hens exposed to different ammonia concentrations under high temperature are shown in Figure 1 and 2. At the high ammonia concentration, blood total antioxidant capacities ($P<0.05$) of birds was lower than the other treatments at 38 wk and blood total antioxidant capacities of all treatments tended to increase from 30 wk (Figure 1). Blood IgG concentrations were low compared with CON when birds were treated with 20 ppm and 45 ppm ammonia (Figure 2). Moreover, supplementation of the ammonia significantly prevented the increase in serum IgG concentration from 33 wk to 38 wk ($P < 0.05$).

The serum corticosterone (CORT) level and luteinizing hormone (LH) concentration of the birds are presented in Figure 3 and 4. Under high ammonia concentrations, the CORT level ($P<0.05$) significantly increased at 30 wk and differed from the other two treatments at 21, 27, 30 and 33 wk. The CORT level tended to increase first and go down with age. As a characterisation of laying performance in terms of blood, LH concentration showed little changes among the three treatments, however, they increased at 30 wk and kept increasing since then. The LH concentration ($P<0.05$) of the CON was significantly higher than the other two treatments from 33 – 38 wk.

This study showed that high concentrations of ammonia impacted the total antioxidative capacities and IgG concentration of laying hens and tended to decrease the blood LH concentration. Our study indicated that high concentration of ammonia was a negative factor for the immune system, increased the incidence of diseases and secondary infections (Anderson *et al.*, 1964; Oyetunde, *et al.*, 1978; Sato *et al.*, 1973).

Conclusions

Results of this study show that high levels of atmospheric ammonia can be detrimental to the production performance and the immune function of laying hens, especially exposed to a chronic heat stress. It is of great significance to allow an increased ventilation rate to control the ammonia level and temperature for the production performance and health of laying hens.

Acknowledgements

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Reference

Anderson, D.P., Beard, C.W., & Hanson, R.P. (1964). The Adverse Effects of Ammonia on Chickens Including Resistance to Infection with Newcastle Disease Virus. *Avian Diseases*, 8(3): 369–379.

Beker, A., Vanhooser, S.L., Swartzlander, J.H., & Teeter, R.G. (2004). Atmospheric Ammonia Concentration Effects on Broiler Growth and Performance. *Journal of Applied Poultry Research*, 13(1): 5–9.

Carlile, F.S. (1984). Ammonia in Poultry Houses: A Literature Review. *Worlds Poultry Science Journal*, 40(2): 99–113.

Charles, D.R., & Payne, C.G. (1966). The influence of graded levels of atmospheric ammonia on chickens. *British Poultry Science*, 7(3): 177–187.

Deaton, J.W., Reece, F.N., & Lott, B.D. (1984). Effect of atmospheric ammonia on pullets at point of lay. *Poultry Science*, 63(2): 384.

Jones, J.B., Burgess, L.R., Ajf, W., & Wathes, C.M. (1997). Behavioural responses of pigs to atmospheric ammonia in a chronic choice test. *Animal Science*, 63(63): 437–445.

Koerkamp, P.W.G.G. (1994). Review on Emissions of Ammonia from Housing Systems for Laying Hens in Relation to Sources, Processes, Building Design and Manure Handling. *Journal of Agricultural Engineering Research*, 59(2): 73–87.

Koerkamp, P.W.G.G., & Bleijenberg, R. (1998). Effect of type of aviary, manure and litter handling on the emission kinetics of ammonia from layer houses. *British Poultry Science*, 39(3): 379–392.

Koerkamp, P.W.G.G., Speelman, L., & Metz, J.H.M. (1998). Litter Composition and Ammonia Emission in Aviary Houses for Laying Hens. Part 1: Performance of a Litter Drying System. *Journal of Agricultural Engineering Research*, 70(4): 375–382.

Lin, X., Zhang, R., Jiang, S., El-Mashad, H., & Xin, H. (2017). Emissions of ammonia, carbon dioxide and particulate matter from cage-free layer houses in California. *Atmospheric Environment*, 152: 246–255.

Oyetunde, O.O., Thomson, R.G., & Carlson, H.C. (1978). Aerosol exposure of ammonia, dust and Escherichia coli in broiler chickens. *Canadian Veterinary Journal La Revue Veterinaire Canadienne*, 19(7): 187–193.

Sato, S., Shoya, S., & Kobayashi, H. (1973). Effect of ammonia on Mycoplasma gallisepticum infection in chickens. *National Institute of Animal Health Quarterly*, 13(2): 45.

Wei, F.X., Hu, X.F., Sa, R.N., Liu, F.Z., Li, S.Y., & Sun, Q.Y. (2014). Antioxidant capacity and meat quality of broilers exposed to different ambient humidity and ammonia concentrations. *Genetics & Molecular Research Gmr*, 13(2): 3117.

Wheeler, E.F., Rwj, W., & Weidenboerner, E. (2000). Evaluation of instrumentation for measuring aerial ammonia in poultry houses. *Journal of Applied Poultry Research*, 9(9): 443–452.

Xin, H., Gates, R.S., Green, A.R., Mitloehner, F.M., Moore, P.A., & Wathes, C.M. (2011). Environmental impacts and sustainability of egg production systems. *Poult Sci*, 90(1): 263–277.

Zhao, L., Hadlocon, L.J.S., Manuzon, R.B., Darr, M.J., Keener, H.M., Heber, A.J., & Ni, J. (2016). Ammonia concentrations and emission rates at a commercial poultry manure composting facility. *Biosystems Engineering*, 150: 69–78.

Zhao, Y., Xin, H., Shepherd, T.A., Hayes, M.D., Stinn, J.P., & Li, H. (2013). Thermal environment, ammonia concentrations, and ammonia emissions of aviary houses with white laying hens. *Transactions of the Asabe*, 56(3): 1145–1156.

Measuring carbon dioxide concentrations in broiler houses

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Abstract

European directive 2007/43/CE establishing standards for the protection of broilers, sets a limit of 3,000 ppm of carbon dioxide (CO_2) concentration not to be exceeded at animal's level, over the entire duration of the flock. Since then, CO_2 concentration sensors are developing in French poultry houses. The purpose of this article is to provide methodological advices for continuous measurement of CO_2 concentrations in a broiler house, by looking at CO_2 commercial sensors' technical specifications and their optimal position in barn. Various CO_2 sensors were compared in a commercial barn. Analysis of accuracy and response time showed that two sensors over five were not suitable to be used for CO_2 monitoring and/or control in poultry houses. The position of the CO_2 sensor at 80 cm +/- 20 cm of height, between water droppers and feeding lines appeared to be the best compromise to measure, not only a representative CO_2 concentration at animal's level, but also of the whole house. However, at the end of the flock, this height can underestimate CO_2 concentrations at animal's level in case of high CO_2 productions by animals and litter. In the observed commercial barns, the horizontal heterogeneity of CO_2 was higher at the beginning of the flock than at the end. These results suggest to use more than one CO_2 sensor for continuous measurements in poultry barns to characterise this heterogeneity. According to the sensors' tests, first level investment should be in high-performance sensor and in its maintenance than purchasing an additional sensor.

Keywords: carbon dioxide, sensor, broiler, gas

Introduction

In poultry houses, carbon dioxide (CO_2) is produced by animal respiration, aerobic degradation of litter materials by microorganisms and combustion of carbonaceous materials, fossil energy and organic matter (Hassouna *et al.,* 2015). Direct combustion heating systems (propane gas combustion with gas emissions inside the house) are an important source of CO_2 production in the broiler house. Carbon dioxide is a molecule that occurs naturally in the atmosphere (~400 ppm in outdoor air). CO_2 is a greenhouse gas, odourless, colourless and heavier than air. The concentration in the indoor air of livestock houses is an indicator of the level of air renewal. In broiler houses, the presence of CO_2 sensors increased since the application of the European regulation on the welfare of broilers (Directive 2007/43/EC). This regulation sets a maximum of 3 000 ppm which must not be exceeded over the entire duration of the breeding period, at animal level. CO_2 can have negative effects on the health, well-being and performance of chickens (McGovern, 2001; Olanrewaju *et al.*, 2008; Reece, 1980). The CO_2 concentration is even higher with the use of direct combustion heating. The objective of this article is (1) to evaluate the performance of CO_2 concentration sensors and (2) to advise on the position of the sensor in a broiler house to be a representative measurement of the average house concentration, at poultry level.

Material and methods

Comparison of different CO_2 concentration sensors

Description of the CO_2 concentration sensors tested

Four CO_2 concentration sensors called 'autonomous' (numbered C1: *Extech $CO_2$10*; C2: *Testo 435-4*; C3: *Vaisala MI70 acquisition unit + GMP252* sensor and C4: *DK660*) were tested as well as one called 'dependent' CO_2 concentration sensor (numbered C5: *Vaisala GMP252*). The 'autonomous' sensor consists of a probe to measure CO_2 concentrations, a data acquisition unit with measurement display and a battery. This type of sensor is generally used for one-off measurements of CO_2 concentrations. The 'dependent' sensor consists only of a probe. It must be connected to a central data acquisition unit or to the electronic controller of the broiler house to access the measurement result. This type of sensor is used for continuous measurements of CO_2 concentrations. The selection criteria for the purchase of CO_2 concentration sensors for poultry house measurements are, not only a measurement range between 0–10,000 ppm to be able to measure certain concentration peaks, but also an accuracy of 100 ppm to obtain the best compromise between the need for precision to characterise the diversity of situations encountered in broiler houses and a level of requirement not too high in order to limit the cost (< €2,000 per unit) of the sensors. The needs in terms of response time of the sensor are related to the use of the sensor. For a broiler house use, a response time qualified as: low (= high reactivity of the sensor) can be considered as less than or equal to 5 minutes; moderate (= average sensor reactivity) between 5 and 10 minutes and high (=low reactivity of the sensor) greater than or equal to 10 minutes. Non-dispersive InfraRed (NDIR) technology has been targeted for the purchase of all sensors since it appears to meet the conditions needed and described above. In addition, it does not require any consumables other than electricity, a low sensitivity to drift over time and little interference with other gases.

Comparison of CO_2 concentration sensor performance in commercial barn

The five sensors were placed together 80 cm above the floor, in the centre of a commercial broiler house, in the presence of the poultry and for the duration of the entire flock (46 days in summer). CO_2 concentrations were measured continuously. The data acquisition frequency for the sensors was less than or equal to three minutes, in order to capture temporal variations in CO_2 concentrations. The CO_2 concentrations of the five sensors were compared to those measured by an INNOVA 1412® gas analyser (infrared photo-acoustic spectrometry; 1% accuracy). The concentrations measured by the analyser was used as the reference for the comparison, hereinafter referred to the 'reference'. The reference sampling was performed at the level of the five sensors tested and the data acquisition frequency was set at three minutes.

Methods for analysing the performance of the sensors tested

In the following (for the understanding of Part 2.1.2), the bias was calculated to determine the accuracy of the sensors. It is the difference in ppm between the measured concentration and the reference concentration. A 'high' accuracy means that the sensor indicates values close to the reference. The bias is low (< 50 ppm). On the contrary, a 'low' accuracy means that the sensor indicates values far from the reference (bias > 150 ppm). The bias is then high in relation to the identified need. The analyses of the measurement accuracy and the calculation of the average CO_2 concentrations were carried out on data corrected by the response time of the sensors. This response time was quantified by evaluating the phase shift between a concentration peak observed by the low-response time reference sensor and the maximum value observed on the sensor considered. The time lag is expressed in minutes.

Position of the CO_2 concentration sensor in a broiler barn

Experimental testing

The tests were conducted in two breeding rooms of 270 m² at the ANSES in Ploufragan. The two rooms were conducted in the same way, with the same number of animals, the same minimum renewal level and direct combustion heating. CO_2 concentrations were recorded in both rooms, in the presence of the broilers over the entire duration of a flock (33 days, from 2 March to 4 April 2017). CO_2 concentrations were measured with a reference device (part 1.1.3) at 10 and 80 cm of height between the water poultry droppers and feeding lines. The evolution of CO_2 concentrations between the different heights and extraction was examined at the beginning and end of the flock.

Field testing

The objective is to check whether the results of the tests under experimental conditions require methodological adaptations according to the type of ventilation, particularly on the number of CO_2 concentration sensors to install and the horizontal position sensor in the house (generally placed in the centre of broiler houses). The tests were conducted in three longitudinally ventilated houses to verify the incidence of heterogeneity compared to the tests performed in the experimental station. The initial hypothesis is that a broiler house in longitudinal ventilation has differences in CO_2 concentrations between the two gables (higher concentrations of extraction gable than the other gable). A first visit was made within the first day of the broiler flock and a second visit during the last week of the animals' life. During each visit the CO_2 concentrations were measured at 10 and 80 cm height for different measurement points in the house. All CO_2 concentration measurements were done with the Vaisala MI70 device equipped with the GMP 252 CO_2 sensor. Each measurement sequence includes measurements every five seconds for two minutes during which the operator is stationary in order to avoid the effect of animal activity on the measured CO_2 concentration. The measurements were repeated for each of the following three measurement points : (1) in the centre of the house; (2) at the air inlet doors 1 m from the wall and (3) at the level of the air extraction at 2 m from the air extraction turbine. Measurements were made between the water poultry droppers and feeding lines. During measurements, the start and stop times of the heating were recorded, as well as the start and end times of the measurement period. Outdoor temperatures and humidity levels were measured before entering the barn. A litter quality rating was also performed during the second visit and at each measurement site (score from 1 [dry and friable] to 5 [totally crusty or wet] rated 5). To assess the spatial variability (horizontal and vertical) of CO_2 concentrations, mean concentrations and associated standard deviations were calculated for the two heights, for the three houses and the three measurement points at the beginning and end of the flock. In order to verify the significance of the observed differences, non-parametric tests were performed at the 5% significance threshold: mean comparison (kruskal.test) for the study of horizontal variability of CO_2 concentrations and multiple mean comparison (kruskaltmc) for the study of vertical variability of CO_2 concentrations.

Results and discussion

Comparison of CO_2 concentration sensors

CO_2 concentrations measured during the commercial barn test (Table 1)

Table 1. Descriptive results over the 46 days of the flock; (REF = reference CO_2 concentrations, measured by the INNOVA 1309® gas analyser ; sd = standard deviation)

	REF	C1	C2	C3	C4	C5
Mean +/- sd (ppm)	1 331 +/- 490	1 618 +/- 691	1 850 +/- 429	1 449 +/- v451	1 057 +/- 450	1 415 +/- 467
Min (ppm)	416	434	498	441	153	464
Max (ppm)	2 836	2 940	2 661	2 928	2 724	3 584
Number of measurements	5,075	6,903	125 514	37 242	133 920	26 800
Acquisition frequency	3 min	3 Min	30 sec	30 sec	30 sec	2 min

During the test, CO_2 concentrations did not exceed 3,000 ppm, by looking at the maximum measured by the reference. The summer comparison period was not conducive to high CO_2 concentrations because air exchange rates are higher in summer with higher outdoor temperatures than in cold periods (Robin *et al.*, 2017). Outliers (less than 300 ppm while the concentration of outdoor air is close to 400 ppm) were observed for C4. For the calculation of averages, outliers have not been deleted. The number of measurements performed for each of the sensors and for the reference is not the same because micro power cuts at the barn caused recording stops and the acquisition frequency was not identical for all sensors. The average CO_2 concentration is higher for the C1 sensor and lower for the C4. The standard deviations are in the 400 - 500 ppm range for all sensors.

Accuracy and response time of the sensors tested (Table 2)

Sensors C3 and C5 have biases of less than 100 ppm. Their accuracy corresponds to the 100 ppm requirement defined above. On the contrary, sensors C1, C2 and C4 have biases greater than 100 ppm. The highest bias is observed for the C4 sensor (422 ppm). It is associated with very high variability. Similarly, the C1 sensor has a high bias, twice as much as the 100 ppm requirement. The C2 sensor is close to the predefined requirements in terms of accuracy and the associated 63 ppm standard deviation. Concerning response time, sensors C2 and C3 have low response time (less than or equal to five minutes). The C4 and C5 sensors have a moderate response time since they are close to 10 minutes. The use of the C4 sensor in broiler houses is clearly not recommended due to its accuracy and the presence of outliers. Similarly, with regard to the feedback from the tests carried out, the shape of the C1 sensor makes it difficult to use in poultry houses (round shape). In addition, C1 has a higher standard deviation than other sensors. The differences in accuracy observed between the sensors can be explained in part by the air heterogeneity and the mixing of the air in conventional houses which could cause the sensors not to measure exactly the same air (even if positioned close to each other). A second reason is the difference in response time of the different sensors. The sensors with low response time will measure puffs of air concentrated in CO_2 at a time close to the time t. On the contrary, a high response time sensor will not measure these puffs. The biases reported by suppliers of the sensors are lower than those calculated in the study (+137 ppm on

average for the accuracies calculated with respect to suppliers' indications). This result is explained by differences in protocols because the suppliers' data are not based on tests carried out in broiler houses. Carrying out the tests in winter would perhaps have allowed more discriminating results to be obtained because CO_2 concentrations are higher in winter. Under the test conditions, sensors C2, C3 and C5 seem to be the most efficient for use in poultry houses.

Table 2. Average observed accuracy (ppm) and response time (minutes), over 46 days of testing, five sensors tested

	C1	C2	C3	C4	C5
Average observed accuracy (deviation from reference) +/- standard deviation (ppm)	181 +/- 99 [with outliers]	136 +/- 63	97 +/- 55	422 +/- 321 [with outliers]	78 +/- 82
Number of values for calculating accuracy	1,166	1,454	1,572	787	4,468
Response time (minutes)	4	3	3	10	9

Position of the CO_2 concentration sensor in the broiler house

Study of the vertical variability of CO_2 concentrations under experimental conditions

At the beginning of the flock, the spatial and temporal variations in CO_2 concentrations measured at different heights and at extraction follow the same pattern. Thus, at the beginning of the flock, the CO_2 concentrations measured at 80 cm are representative of those measured at 10 cm from the floor and therefore of what animals breathe. They also evolve in the same way as those measured at extraction, so they are representative of the overall atmosphere of the house. At the end of the flock, the CO_2 concentrations measured at 80 cm and those measured at extraction follow the same evolutions. Thus, as at the beginning of the flock, concentrations measured at 80 cm are representative of the overall atmosphere of the barn for both rooms. CO_2 concentrations measured at 10 cm do not follow the same evolution as the 80 cm and extraction measurements. Measurements at 10 cm are greater than those at 80 cm and at extraction. These differences can be explained by a degradation of the litter at the end of the flock, probably caused by the absence of collectors under the water droppers. This litter fermentation generated a CO_2 production at 10 cm, compared to 80 cm from the ground. Thus at the end of the flock, a measurement at 80 cm of the ground cannot assess fluctuations in CO_2 concentrations caused by litter degradation.

Variability of CO_2 concentrations in commercial broiler houses

Beginning of the flock

Vertical variability — CO_2 concentrations measured at 80 cm are significantly higher than those measured at 10 cm from the floor for E1 and E3 farmers (except in the centre of the house where the measurements at 10 and 80 cm are not significantly different). These two farmers have direct combustion heating at the start of the flock (potential thermal

stratification due to the low air renewal at the beginning of the flock combined with a high demand for heating). On the contrary, for E2 farmer, there is no significant difference between the measurements at 10 and 80 cm, in the centre and at the air extraction, potentially related to the use of indirect combustion heating associated with air circulation by hot water unit heaters. At the beginning of the flock, on the sample of the three farms studied, it would seem that concentrations at 10 cm are higher in houses with direct combustion heating, compared to those at 80 cm.

Table 3. average CO_2 concentrations (ppm) measured at 10 cm and 80 cm for each of the three locations in the house in the three farms during the poultry start-up period. [Result at 5% significance level: P < = Significant; NS = Not Significant]

Measuring point	Farm	10 cm	80 cm	Result
Center	E1	2,735	2,782	P<0,01
Entrance	E1	2,352	2,740	P<0,01
Extraction	E1	2,217	2,454	P<0,01
Center	E2	1,824	1,810	NS
Entrance	E2	1,695	1,679	P<0,05
Extraction	E2	1,772	1,757	NS
Centre	E3	4,172	4,169	NS
Entrance	E3	4,694	4,903	P<0,01
Extraction	E3	4,984	5,157	P<0,01

Horizontal variability — At the beginning of the flock for two of the three farms (E1 and E3), CO_2 concentrations measured in the centre of the house, at the air inlet and at the air extraction are different for both the 10 and 80 cm measurements. The same result is observed for the E2 farm but only for measurements made at 80 cm from the floor. For the E2 farm, at 10 cm from the ground, CO_2 concentrations measured in the centre of the barn and at the air extraction were not significantly different (at the 5% threshold). These observations are probably due to the air brewing provided by the heating systems (hot water unit heaters) at the beginning of the flock. For E1 farmer, CO_2 concentrations are significantly higher than the air inlet compared to the air extraction for measurements made at 10 and 80 cm from the floor (+210 ppm on average for air inlet compared to air extraction. This result can be explained by the distance of one metre from the wall for the measurement at the air inlet (poor homogeneity of the air near the wall and under the air inlet hatch), but it is observed for breeding E1 farmer only. For E2 and E3 farmers, CO_2 concentrations are higher than the air extraction compared to the air inlet (+175 ppm on average for both farms). Measurements of CO_2 concentrations are higher in the centre of the house than at the air extraction and air intake for the farmer E1 (+318 ppm for measurements at the centre than at the extraction and intake of air). This may be related to the switching on of the heating system during the measurements and to a less efficient air circulation. In addition, this farm is equipped with an auxiliary gas heating system at start-up (direct combustion heater). In contrast, for E3 farmer, CO_2 concentrations are lower in the centre and higher during extraction (for measurements at 10 and 80 cm). In this farm, the house is equipped with a direct combustion heater, there is more heterogeneity of CO_2 concentrations between the three measurement points, compared to the other two houses (in indirect combustion heating). On the contrary,

the CO_2 concentrations measured in farm E2 with indirect combustion heater, were less heterogeneous for measurements at 10 cm from the floor. These observations are probably due to the brewing provided by the heater (hot water unit heaters) at the beginning of the flock. Thus, these measurements show a horizontal heterogeneity of CO_2 concentrations in the three houses studied, confirming the initial hypothesis. This result may suggest the addition of sensors to take into account this horizontal variability. However, this variability remains close to the bias that can be observed between the sensors and the purchase of additional sensor(s) represent(s) a significant cost for the farmer. It is therefore advisable to invest in a high-performance sensor rather than an additional sensor.

End of the flock

Vertical variability — At the end of the broiler flock, the average CO_2 concentrations measured at 10 cm and 80 cm from the floor and each of the measurement points are significantly different. For E1 and E2 farmers, the measurements at 10 cm are significantly higher than those at 80 cm. This can be explained by a poor quality litter, which is wet and produces CO_2 and are noted four at the measurement site in the farm E1. On the other hand, in farm E2, the litter is rated one (dry and friable litter). This result can be explained by a potential CO_2 gradient from animal respiration and less efficient air brewing. Concentrations are higher at 10 cm from the ground and reflect litter degradation, compared to measurements at 80 cm, in one of the three farms. The results obtained in the experimental station are confirmed in one farm only. Thus, if the sensor is positioned 80 cm above the ground, CO_2 concentrations at animal level will tend to be underestimated. In contrast, in E3 farmer, CO_2 concentrations measured at 80 cm are significantly higher than those measured at 10 cm from the floor, except for measurements made at the level of air extraction.

Horizontal variability — For the three farms, the CO_2 concentrations are significantly higher than the air inlet compared to the air extraction, for measurements at 10 cm and 80 cm from the floor, except for the farm E1 for measurements at 80 cm (NS). This result can be explained, at the beginning of the flock, by the protocol used to take the measurement. At the end of the flock, the brewing and air circulation increase may explain this result. The CO_2 concentrations measured in the centre of the house are systematically lower than those measured near the air inlet, however, these differences are not significantly different for the farm E1 for the 10 cm measurements and for the farm E3 for the 80 cm measurements. For the three farms, the CO_2 concentrations are significantly different between the centre of the house and the air extraction, for measurements at 10 cm and 80 cm from the floor, except for the E2 farm for measurements at 80 cm where the difference is not significant. The horizontal heterogeneity of CO_2 concentrations at the end of the flock is less marked than at the beginning of the flock for the three farms studied. This suggests that it could be useful to have more than one sensor at the beginning of the flock.

Table 4. Average CO_2 concentrations (ppm) measured at 10 cm and 80 cm for each of the three locations in the house in the three farms at the end of the poultry flock. [Result at 5% significance threshold: P < = Significant]

Measuring point	Farm	10 cm	80 cm	Result
Centre	E1	2,885	2,363	P<0,01
Entrance	E1	2,973	2,693	P<0,01
Extraction	E1	2,703	2,614	P<0,01
Centre	E2	1,619	1,337	P<0,01
Entrance	E2	1,871	1,574	P<0,01
Extraction	E2	1,356	1,299	P<0,01
Centre	E3	2,948	3,111	P<0,01
Entrance	E3	2,995	3,192	P<0,01
Extraction	E3	3,050	2,973	P<0,01

Conclusions

The test of CO_2 sensors of a same technology (non-dispersive infrared) shows that two of the five sensors are not recommended to use in poultry houses. Tests carried out in the experimental station suggest an optimal position of the CO_2 sensor at the beginning of rearing at 80 cm +/- 20 cm from the ground, between the water droppers and the feeding lines. At the end of the flock as well as at the beginning, this height allows a representation of the overall CO_2 concentration of the barn but may underestimate concentrations at the animals' level, at the end of the lot. This result may suggest adding a sensor at animal level in addition to one at 80 cm (careful to ensure that the sensor is protected to avoid damage from animals). The horizontal heterogeneity of CO_2 concentrations at the end of the flock is less pronounced than at the beginning, where the differences between the centre, the air outlet and the air extraction are significant. Again, this result may suggest adding additional sensors at the beginning of the broiler flock. However, according to the sensors testing, it is better to invest in a quality sensor and its maintenance than in a large number of sensors.

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References

CIGR (1984). *Report of working group on Climatization of Animal Houses*. Editors: Scottish Farm Building Investigation Unit. Craibstone, Aberdeen, Scotland. ISBN 0 902433 33 4. 80 pages.

Bonnard, N., Brondeau, M-T., Falcy, M., Jargot, D., Miraval, S., Protois, J-C. and Scheneider, O. (2005). Fiche toxicologique INRS Dioxyde de carbone FT 238.

McGovern, R.H., Feddes, J.J.R., Zuidhof, M.J., Hanson, J.A., and Robinson, F.E. (2001). Growth performance, heart characteristics and incidence of ascites in broilers in response to carbon dioxide and oxygen concentrations. *Canadian Biosystems Engineering,* 43: 4.1–4.6.

Hassouna, M., Eglin, T., Cellier, P., Colomb, V., Cohan, J-P. (2015). Mesurer les émissions gazeuses en élevage: gaz à effet de serre, ammoniac et oxydes d'azote. *INRA-ADEME* (FR), 2-7380-1375–9.

Olanrewaju, H., Dozier, W.A., Miles, D., Lott, B.D. (2008). Growth performance and physiological variables for broiler chickens subjected to short-term elevated carbon dioxide concentrations. *International Journal of Poultry Science,* 7(8): 738–742.

Reece, F. and Lott, B. (1980). Effect of carbon dioxide on broiler chicken performance. *Poultry Science*, 59(11): 2400–2402.

Robin, P., Amand, A., Nicolas, C., Chevalier, D., Gallot, S., Pigache, E. and Keita, A. (2017). Modélisation thermique des bâtiments d'élevage de poulets de chair en vue d'optimiser le choix des équipements et les paramètres de régulation. *12èmes journées de la recherché avicole et palmipèdes à Foie Gras*, Tours.

Thermal rearing environment affects heat emission by laying hens

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Abstract

The effect of different thermal rearing environments associated with diets with two energetic levels in the heat emission by laying hens was studied. 18 laying hens, Bovans White, with 95 weeks of initial age were housed in groups of three birds per cage, equipped with feeder and nipple drinker and submitted to six factorial treatments 2 × 3 (rations with two energy densities × three thermal environments). The feed rations had similar composition, differing in energy densities, obtained by inclusion of soybean oil: ration with 2,750 kcal of metabolizable energy (ME) and feed with 3,250 kcal ME. The feed and water were supplied *ad libitum*, and each room had a thermal environment type, being Room 1 - thermoneutral environment, with an average temperature (AT) of 24.3 °C and relative humidity (RAH) of 62.3%; Room 2 - hot environment, with 30.2 °C AT and 58.8% RAH; and Room 3 - cold environment, with 17.7 °C AT and 98.5% RAH. The heat emission was measured once a day, by cage and by one of the birds, during the whole experimental period, using the Hotter HT3 thermographic camera, with a coefficient of emissivity of 0.96, and through the software *IR Reporter* V.1.0. The rearing environment affected the heat emission by the bird ($P < 0.05$). The highest temperatures were observed in hens housed under heat stress, followed by the thermoneutral and, finally, the cold rearing environment. There was an interaction between environment and time of accommodation ($P = 0.026$), with reduction of this variable in cold environments and increase in hot environments.

Keywords: cold, hot, thermoneutral, time exposition

Introduction

The Brazilian layers' farming is continually growing. Since 2010, there has been a 35.8% increase in egg production (ABPA, 2017). Such a feature is due, in particular, to the development in technologies by which the segment has adopted, in addition to improvements in other factors such as genetics, nutrition, and health (Wang *et al.*, 2017). In the field of layer nutrition, an important step was the introduction of metabolizable energy studies in the 40s by Fraps *et al.* (1944), through the development of the digestibility techniques and determination of the diets nutritional composition (Sakomura *et al.*, 2015). The progress went on up to the verification of the effect of the environment on the consumption and digestibility of the food, where it was observed the worsening of these parameters when the bird is in thermal stress (White & Hanigan, 2015; Liu *et al.*, 2016).

The present study aimed to verify the immediate effect of different thermal environments associated with diets with two energetic levels in the parameters of behavior of laying hens at the end of laying.

Material and methods

Experimental data

This study was carried out according to the ethical principles and was approved by the local Research Ethics Committee (CEUA/UNIGRAN no. 009/16). The study was conducted

in Dourados, State of Mato Grosso do Sul, Brazil -22.197157 Lat.; -54.938371 Log.), from 8 – 16 March 2017, for nine days with five days for adaptation of birds to cages, diets, and air conditioning and four days of data collection. For that, 18 Bovans White chickens were used at the end of laying period, with initial age of 95 weeks. The birds were housed in groups of three birds per cage, which were 41 cm wide by 61 cm long and 41 cm height and were equipped with a trough-type feeder and nipple-type drinker.

The tested feed had similar composition, differing in energy densities, obtained by including soybean oil: feed with 2750 kcal of metabolizable energy (ME); and feed with 3,250 kcal of ME. The feed and water were supplied *ad libitum*, and each air-conditioned room simulated a thermal environment, where:

- *Room 1:* thermoneutral environment (TE), with an average temperature of 24.3 °C and 62.3% relative humidity;
- *Room 2:* hot environment (HE), with an average temperature of 30.2 °C and 58.8% relative humidity;
- *Room 3:* cold environment (CE), with an average temperature of 17.7 °C and 98.5% relative humidity.

Therefore, the experiment was performed in a split – plot design with the main plots as the combination of two energy levels and three environmental temperatures, and the days as secondary plots.

Heat emission analysis

The heat emission was measured once a day, by cage and by one of the birds, during the whole experimental period, using the Hotter HT3 thermographic camera, with a coefficient of emissivity of 0.96, and through the software *IR Reporter* V. 1.0, generating an average value of heat emission for each bird.

Statistical analysis — Data were tested for the normality of the residues and homogeneity of the variances using *PROC UNIVARIATE*. The model used was:

$$Y_{ijl} = \mu + A_i + D_j + time_k + (D_j{*}A_i) + d_{ijk} + (A_i{*}\,time_k) + (D_j{*}\,time_k) + e_{ijl} \quad (1)$$

where μ is overall average, A_i is effect of the environment, D_j is effect of diet, $time_k$ is effect of time, d_{ijk} is error associated to main parcel, A_i . $time_k$ is effect of time and environment interaction, D_j * $time_k$ is effect of diet and environment interaction, e_{ijl} is error.

The data were submitted to the analysis of variance by the *PROC MIXED* of SAS 9.0, adopting a level of significance of 5%.

Results and discussion

The rearing environment affected the heat emission by the bird ($P < 0.05$). The highest temperatures for these variable were observed in hens housed under heat stress, followed by the thermoneutral and, finally, the cold rearing environment. There was an interaction between environment and time of accommodation ($P = 0.026$) with reduction of the heat emission in cold environments and increase in hot environments, regardless of the time, demonstrating the constancy in the temperature of each environment.

Table 1. Heat emission (°C) by the bird according to the diets and thermal environments

Variables	Environment**					
	Cold		Thermoneutral		Hot	
	Metabolizable energy***					
	2,750 kcal	3,250 kcal	2,750 kcal	3,250 kcal	2,750 kcal	3,250 kcal
Heat emission (°C)	21.2[C]	21.9[C]	28.6[B]	28.3[B]	32.2[A]	31.3[A]
ASE*	0,70					
P Value	Diet	0,716				
	Environment	0,0001				
	Interaction	0,597				

*Average standard error; ** Averages followed by different capital letters (A, B, C) in the same line with the effect of the Environment by the Adjusted Tukey Test ($P < 0.05$); *** Averages followed by different lowercase letters (a, b) in the same line with Diet Effect by Adjusted Tukey Test ($P < 0.05$).

The higher temperature of rearing environment affects animal health, due to the reduction of the feed consumption, and the reverse occurs at low temperatures (White & Hanigan, 2015). The expression of the hypothalamic mRNA of the gonadotropin-inhibiting hormone (GnIH) is altered by an increase in temperature, when above the thermoneutral range (Chowdhury *et al.*, 2012). Such impact acts by inhibiting anorexigenic neuropeptide, that is, appetite stimulant, reflecting in a reduction in food intake and increase in body temperature. This effect coincides with the results obtained in this study, in which the environment affected the body temperature and the heat emission by the bird, where the highest temperatures for these two variables were observed in hens housed in a hot environment, followed by thermoneutral and, for last, the cold. Therefore, in this case, the expression of Gonadotrophin Inhibitor Hormone (GnIH) was reduced when the birds were exposed to high temperatures and, due to the orexigenic effect of this hormone, the food consumption was also inhibited.

Acknowledgements

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Conclusions

The thermal environment affects heat emission by laying hens and temperatures above the thermoneutrality is more stressful and deleterious to laying hens than the cold environment. The thermoneutral environment is recommended for better layer welfare.

References

ABPA. Annual Report of the Brazilian Animal Protein Association (ABPA) 2017. 2017. 133 p.

Chowdhury, V.S., Tomonaga, S., Nishimura, S., Tabata, S., Cockrem, J.F., Tsutsui, K. and Furuse, M. (2012). Hypothalamic gonadotropin-inhibitory hormone precursor mRNA is increased during depressed food intake in heat-exposed chicks. Comparative Biochemistry Physiology - Part A: *Molecular & Integrative Physiology*, 162(3): 227–233.

Fraps, G.S. (1944). Maintenance requirements of chickens and productive energy of feeds as related to age. Conner, A.B., organizator. San Angelo, Texas, USA: Agricultural and Mechanical College of Texas. Bulletin 665. 34 pp.

Liu, Q.W., Feng, J.H., Chao, Z., Chen, Y., Wei, L.M., Wang, F., Sun, R.P. and Zhang, M.H. (2016). The influences of ambient temperature and crude protein levels on performance and serum biochemical parameters in broilers. *Journal of Animal Physiology and Animal Nutrition,* 100(2): 301–308.

Sakomura, N., Gous, R.M., Kyriazakis, I. and Hauschild, L. (2015). Nutricional modelling for pigs and poultry. 1 ed. Sakomura, N., Gous, R.M., Kyriazakis, I. and Hauschild, L., organizators. Jaboticabal, São Paulo, Brazil: CAB International. 318pp.

Wang, J., Yue, H., Wu, S., Zhang, H. and Qi, G. (2017). Nutritional modulation of health, egg quality and environmental pollution of the layers. *Animal Nutrition,* 3(2): 91–96.

White, R.R. and Hanigan, M.D. (2015). Modelling cross-species feed intake responses to thermal stress. *Journal of Agricultural Science,* 154(1): 136–150.

Session 11

Location and Tracking of Animal Movement (1)

Automated phenotyping of swine behaviour using image analysis: A systematic review

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Abstract

Large scale phenotyping of animal behaviour traits is time consuming and has led to increased demand for technologies that can automate these procedures. Automated tracking of animals has been successful in controlled laboratory settings but tracking animals in large groups in highly variable farm settings presents challenges. The aim of this review was to provide a systematic overview of the advances that have occurred in automated, high throughput image detection of swine behavioural traits with welfare and production implications. Peer-reviewed publications written in English were reviewed systematically following Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines. After identification, screening, and assessment for eligibility, 63 publications met these specifications and were included for qualitative synthesis. Data collected from the papers included camera specifications, housing conditions, group size, algorithm details, procedures and results. Most studies utilised standard digital cameras (n = 54) for video collection, with increasing 3-D monitoring in papers published in 2014 and beyond. Papers included pigs in production stages ranging from recently weaned piglets to mature breeding sows. Behaviours recorded included activity level, area occupancy, aggression, gait scores, resource use, and posture, among others. Our review revealed many overlaps in methods applied to analysing behaviour, and most studies started from scratch instead of building upon previous work. Training and validation sample sizes were generally small (mean = 10) and testing took place in relatively controlled environments. To advance our ability to automatically phenotype behaviour, future research should build upon existing knowledge and validate technology under commercial settings.

Keywords: Precision livestock farming, pig, behaviour, automated, vision analysis

Introduction

Livestock caretakers routinely monitor animal behaviour to assess health and welfare of animals in their care. Animal suffering can be minimised through early detection of illness, injury, or damaging behaviours such as aggression. Societal concerns continue to rise over the treatment of animals raised for meat, thus efficient monitoring of animals is essential for sustainability. Modern day production of swine often means housing animals in large groups, making it challenging for farm staff to inspect animals appropriately at the individual level. Detection of individual behaviour also has applications for research and selection of breeding stock. Behavioural phenotyping traditionally relies on direct observation or video capture and playback, which can be costly, time consuming, and prone to errors. Machine vision could allow for automated individual behavioural phenotyping through installation of cameras within swine facilities. Automated behavioural detection systems continue to develop, however, much of the testing of these programs has been performed in controlled environments. In practice, swine facilities are dynamic and messy environments, such as variable lighting, uneven floor colorations from faeces or bedding, multi-coloured pigs, or occlusions from pen objects or other pigs. Success of these programs in complex farm environments is largely unknown and needs to be addressed. The aim of this review was to provide a systematic overview of the advances that have occurred in automated, high-throughput image detection of swine behavioural traits with welfare and production implications.

Materials and methods

Search strategy and selection of publications

Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines were followed for this review. The following databases were searched for relevant peer-reviewed and English written publications: Google Scholar, Web of Science, PubMed, ARICOLA, and ACM Digital Library. An additional search for 'grey literature' was performed using Google. Our full study encompasses automated visual recording of behaviour of all livestock species, thus our initial search used the following search terms: autom* + behavio* + livestock; autom* + behavio* + pig; autom* + behavio* + video + livestock; autom* + behavio* + video + pig; behavio* + detection + pig; autom* + behavio* + video detection + pig. This initial search returned 350 potentially relevant papers, with an additional 98 articles added after snowballing. Removal of duplicate articles left 340 articles for abstract screening, which then resulted in 153 articles for full-text assessment. An additional 45 papers were excluded due to not meeting selection criteria. From these 108 articles, 63 were focused on swine and thus were included in this qualitative synthesis.

Data extraction

Experimental details were collected from each publication including information on camera specifications, housing conditions relevant to recording, group size, algorithm details, procedures, and results. The majority of studies were conducted on groups of growing pigs, although some studies were conducted on singly housed sows or suckling piglets. Standard, digital cameras were the most common camera type used (n = 54), while more recent studies have begun to explore the use of depth cameras (n = 10). A top-down view was the most common camera position (55 studies), while five studies used an angled top-down view, three studies viewed animals from the side, and one study did not mention camera location. All monitoring took place in indoor environments. Eighteen studies were conducted on commercial farms, 23 in indoor research facilities, and 21 were conducted in equipped test pens. Two studies observed pigs in a slaughter house. Floor materials, and thus background colour, varied greatly among studies. Most studies had concrete flooring (n = 35), either solid, partially slatted, or fully slatted. Nine studies had slatted floors of numerous colours, while six studies had floors bedded with a substrate. Fourteen studies failed to mention any details on floor type, which was surprising given how substantial background colour is to the functioning of machine vision algorithms. Of the studies that mentioned lighting conditions, most provided vague descriptions such as 'varied', 'sunny', or 'natural'. Group sizes used for testing were generally small (average = 10.3 individuals, median = 9) and ranged from one to 40 pigs in a pen. Total study population size was larger (average = 43.4, median = 17, range = 1-667). Information generated by the tracking software varied from the basics of segmentation of individuals (11 studies), to tracking activity or resource use (29 studies), detection of postures or gait scores (10 studies), up to more advanced detection of specific behaviours (11 studies). Out of these studies, only three were able to successfully track an individual animal within a group setting.

Results and discussion

Detection of behaviour typically consists of a series of computational steps. Segmentation, or the process of distinguishing individual animals from their background, is a necessary initial step in machine vision methodology. These techniques often segment pixels based upon colour, intensity, texture, and/or location. Pig activity levels and location within a pen can be estimated using pixel analysis obtained from digital video. An occupation index can be obtained by measuring the percentage of pixels above a defined threshold. This can be done at the pen level, or on focal regions within the pen. An activity index can also be obtained by measuring the amount of pixel change between consecutive images.

Optical flow analysis can also estimate motion and relative velocity of an object through comparing consecutive frames. Through combinations of segmentation and motion analysis techniques, individual pigs may be identified and tracked within their pen. The ability to link phenotypes to individual identifications is crucial to automated behavioural detection systems. The following sections will address results arising from various methods utilized for automating detection of specific behaviours with welfare and production implications.

Gait score estimation and posture detection

Lameness in pigs is a significant concern for producers. To develop a vison system capable of evaluating pig locomotion, Kongsro (2013) used object extraction which then generated a map image using MATLAB® software (The MathWorks Inc., 2010). They then characterized structural soundness through multivariate image analysis. Alternatively, Weixing and Jin (2010) utilized image sequences captured from a side-view camera to model gait information based upon movement of body points and joint angles. Motion analysis was then performed after extracting these key features in order to classify abnormal gait.

Depth information provided by 3D cameras has also been used for automatic detection of pig gait (Stavrakakis *et al.*, 2015). A marker was attached to each pig's neck as it walked under a runway, and the trajectory of this marker was compared between a basic Kinect system, and a 'gold standard' six camera Vicon system (Vicon T20, Oxford, UK). Good agreement was found between the systems, but only if the marker was used, suggesting that the system would need further development for use in a commercial farm setting as unmarked pigs are more feasible. Two studies by Zhu *et al.* detected pig posture through Zernike moments (image property representation with high accuracy for detailed shapes and magnitudes invariant under rotation) and support vector machines (supervised learning models) (Zhu *et al.*, 2015b) and thresholding depth images to detect standing (Zhu *et al.*, 2015a). Depth cameras have also been utilised to detect posture information in lactating, crated sows (Lao *et al.*, 2016; Zheng *et al.*, 2018). Depth cameras have the advantage of functioning in the absence of light and have been used to detect standing pigs at night (Kim, Chung, *et al.*, 2017a; Kim, Choi, *et al.*, 2017b). As an early-warning sign of tail biting, D'Eath *et al.* (2018) used a proprietary system with industrial cameras robust to typical pig farm environments to accurately (73.9%) detect tail posture.

Behavioural detection

Through different combinations of segmentation techniques, location, and posture information, more complex pig behaviours can be detected through image analysis. One study was able to detect respiration by implementing a concave and convex recognition method (Weixing and Zhilei, 2010). Through use of the animal tracking program EthoVision (Noldus *et al.*, 2001), pigs lying proximity, orientation (parallel, antiparallel, or perpendicular), as well as nosing around the ear of another pig were able to be detected (Šustr *et al.*, 2001). In a series of papers, Nasirahmadi *et al.* (2015) developed a machine vision approach to record pig lying behaviour. After segmentation, moving pigs were eliminated using previously discussed methods. The clustering of the remaining lying pigs was defined as close, normal, or far using Delaunay triangulation. This, along with pig location within the pen was correlated with changes in pen temperature. Nasirahmadi *et al.* (2017a) built on this approach by using a neural network with a back propagation algorithm to find the optimal combination of different metrics from the Delaunay triangulation to best describe the different lying patterns of pigs to identify cool, ideal or warm temperatures. Nasirahmadi *et al.* (2017b) strategically altered pen activity through the provision of feed to test the performance of their algorithm. In a different application of their approach, to detect mounting behaviour, Nasirahmadi *et al.* (2016) repeated their approach to fitting ellipses to monochrome pig outlines. Greyscale thresholding fails to separate mounted

pigs, and the model tries to fit an ellipse to a mounted pair as though it were a single pig. This ellipse is then either unexpectedly long (mounting from rear), or too wide (mounting from side- T shaped outline), allowing mounted pairs to be identified. Kashiha *et al.* (2013) employed an innovative approach to estimate water use of fattening pigs in real-time.

Pig aggression, another behaviour critical to animal welfare and production efficiency, has been successfully detected through machine vision techniques. Oczak *et al.* (2014) used the output of this relatively simple pixel based 'activity index' as the basis for a system to detect activity which is indicative of aggressive behaviour (fighting) in pigs. Features such as the maximum, minimum and average activity over successive seven second periods were used as inputs to multilayer feed forward neural network, which was trained with 24 h of video of unfamiliar pigs mixed into a new group and was able to learn the characteristic activity patterns which indicate aggression. It was over 90% accurate at identifying aggression in a different group, however the system was not tested against other high activity events such as locomotor play by young pigs in a new pen. From the same group, Viazzi *et al.* (2014) weaned piglets into groups of twelve pigs per pen and recorded the interactions over sixty hours to detect aggression in pigs. Aggressive interactions were labelled manually and related to the Motion History Image of which the mean intensity and the occupation index were used. Linear Discriminant Analysis was then used to classify aggressive interactions. The algorithm resulted in 89% accuracy when validated against the manually labelled data. The work on aggression was continued by Chen *et al.* (2017), using a vision-based method to separate fighting pigs from the other individuals in the pen. Chen and co-authors studied the acceleration between adjacent frames, as aggression typically consists of rapid movements. The algorithm could reliably detect high velocity aggression (97% accuracy) and medium aggression (95.8%). The risks, however, are that low velocity aggression is not detected accurately and that high velocity non-aggressive behaviours such as play are misclassified as aggression. In a contrasting approach Lee *et al.* (2016) segmented standing pigs and tracked using Euclidian distance between subsequent frames under some threshold, and an index algorithm developed by Zuo *et al.* (2014). Various movement metrics (features) were then generated (minimum, maximum, mean and standard deviation of velocity, and distance between the pigs). They then used a machine learning approach, training support vector machines with instances of different types of aggressive behaviour manually labelled by a human observer. There were two support vector machines used in sequence- one to identify aggression from non-aggression (which was 95.7% accurate in this study), and the second to identify sub-types of aggression such as head knocking (88.9%) and chasing (91.5%).

Conclusions

Rapidly evolving camera technology and advancements in algorithm development are making automated detection of pig behaviour a reality, as apparent in this review. Solutions for uneven lighting, poor pig contrast, and occlusions have been developed. However, knowledge gaps remain that need to be addressed before these methods can be applied to real farm environments. One of the most significant remaining issues is accurately retaining individual identification of unmarked individuals in complex group settings. Additionally, validation of these behavioural detecting algorithms needs to be performed on larger groups of animals. A further, more in-depth review of technologies covering all livestock species will be conducted by this team to provide recommendations for the way forward to most effectively develop and implement these systems on farms.

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References

Chen, Chen, Weixing Zhu, Changhua Ma, Yizheng Guo, Weijia Huang, and Chengzhi Ruan (2017). Image Motion Feature Extraction for Recognition of Aggressive Behaviors among Group-Housed Pigs. *Computers and Electronics in Agriculture,* 142, Elsevier B.V.: 380–87.

D'Eath, Richard B., Mhairi Jack, Agnieszka Futro, Darren Talbot, Qiming Zhu, David Barclay, and Emma M. Baxter (2018). Automatic Early Warning of Tail Biting in Pigs : 3D Cameras Can Detect Lowered Tail Posture before an Outbreak. *PLoS ONE,* 13(4): 1–18.

Kashiha, Mohammadamin, Claudia Bahr, Sara Amirpour Haredasht, Sanne Ott, Christel P.H. Moons, Theo A. Niewold, Frank O. Ödberg, and Daniel Berckmans (2013). The Automatic Monitoring of Pigs Water Use by Cameras. *Computers and Electronics in Agriculture*, 90, Elsevier B.V.: 164–69.

Kim, Jinseong, Younchang Choi, Miso Ju, Jawon Sa, Yongwha Chung, Daihee Park, and Hakjae Kim (2017a). Lying-Pig Detection Using Depth Information. In: *ICACS '17*, 40–43.

Kim, Jinseong, Yeonwoo Chung, Younchang Choi, Jaewon Sa, Heegon Kim, Yongwha Chung, Daihee Park, and Hakjae Kim (2017b). Depth-Based Detection of Standing-Pigs in Moving Noise Environments. *Sensors*, 17(12): 2757.

Kongsro, Jørgen (2013). Development of a Computer Vision System to Monitor Pig Locomotion. *Open Journal of Animal Sciences*, 3(3): 254–60.

Lao, F., T. Brown-Brandl, J . P. Stinn, K. Liu, G. Teng, and H. Xin (2016). Automatic Recognition of Lactating Sow Behaviors through Depth Image Processing. *Computers and Electronics in Agriculture,* 125, Elsevier B.V.: 56–62.

Lee, Jonguk, Long Jin, Daihee Park, and Yongwha Chung (2016). Automatic Recognition of Aggressive Behavior in Pigs Using a Kinect Depth Sensor. *Sensors*, 16(5): 631.

Nasirahmadi, A., O. Hensel, S.A. Edwards, and B. Sturm (2017a). A New Approach for Categorizing Pig Lying Behaviour Based on a Delaunay Triangulation Method. *Animal* 11(1): 131–39.

Nasirahmadi, Abozar, Sandra A. Edwards, Stephanie M. Matheson, and Barbara Sturm (2017b). Using Automated Image Analysis in Pig Behavioural Research: Assessment of the in Fl Uence of Enrichment Substrate Provision on Lying Behaviour. *Applied Animal Behaviour Science,* 196, Elsevier: 30–35.

Nasirahmadi, Abozar, Sandra Edwards, Uwe Richter, and Barbara Sturm (2015). Automatic Detection of Changes in Pig Group Lying Behaviour Using Image Analysis. In: *2015 ASABE Annual International Meeting*.

Nasirahmadi, Abozar, Oliver Hensel, Sandra A. Edwards, and Barbara Sturm (2016). Automatic Detection of Mounting Behaviours among Pigs Using Image Analysis. *Computers and Electronics in Agriculture,* 124, Elsevier B.V.: 295–302.

Noldus, Lucas P.J.J., Andrew J. Spink, and Ruud A.J. Tegelenbosch (2001). EthoVision: A Versatile Video Tracking System for Automation of Behavioral Experiments. *Behavior Research Methods, Instruments, & Computers,* 33(3): 398–414.

Oczak, Maciej, Stefano Viazzi, Gunel Ismayilova, Lilia T. Sonoda, Nancy Roulston, Michaela Fels, Claudia Bahr, *et al.* (2014). Classification of Aggressive Behaviour in Pigs by Activity Index and Multilayer Feed Forward Neural Network. *Biosystems Engineering* 119: 89–97.

Stavrakakis, Sophia, Wei Li, Jonathan H. Guy, Graham Morgan, Gary Ushaw, Garth R. Johnson, and Sandra A. Edwards (2015). Validity of the Microsoft Kinect Sensor for Assessment of Normal Walking Patterns in Pigs. *Computers and Electronics in Agriculture,* 117, Elsevier B.V.: 1–7.

Šustr, P., M. Špinka, S. Cloutier, and R.C. Newberry (2001). Computer-Aided Method for Calculating Animal Configurations during Social Interactions from Two-Dimensional Coordinates of Color-Marked Body Parts. *Behavior Research Methods, Instruments, & Computers*, 33(3): 364–70.

Viazzi, S., G. Ismayilova, M. Oczak, L.T. Sonoda, M. Fels, M. Guarino, E. Vranken, J. Hartung, C. Bahr, and D. Berckmans (2014). Image Feature Extraction for Classification of Aggressive Interactions among Pigs. *Computers and Electronics in Agriculture,* 104, Elsevier B.V.: 57–62.

Weixing, Zhu, and Zhang Jin. (2010). Identification of Abnormal Gait of Pigs Based on Video Analysis. *2010 Third International Symposium on Knowledge Acquisition and Modeling*, 394–97.

Weixing, Zhu, and Wu Zhilei (2010). Detection of Porcine Respiration Based on Machine Vision. In 3rd *International Symposium on Knowledge Acquisition and Modeling*, 398–401.

Zheng, Chan, Xunmu Zhu, Xiaofan Yang, Lina Wang, Shuqin Tu, and Yueju Xue (2018). Automatic Recognition of Lactating Sow Postures from Depth Images by Deep Learning Detector. *Computers and Electronics in Agriculture,* 147, Elsevier: 51–63.

Zhu, Qiming, Jinchang Ren, David Barclay, Samuel McCormack, and Willie Thomson (2015a). Automatic Animal Detection from Kinect Sensed Images for Livestock Monitoring and Assessment. In: *2015 IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing*, 1154–57. IEEE.

Zhu, Weixing, Yan Zhu, Xincheng Li, and Dengting Yuan (2015b). The Posture Recognition of Pigs Based on Zernike Moments and Support Vector Machines. In: *2015 10th International Conference on Intelligent Systems and Knowledge Engineering (ISKE)*, 480–84.

Zuo, Shangsu, Long Jin, Yongwha Chung, and Daihee Park (2014). An Index Algorithm for Tracking Pigs in Pigsty. In: *Proceedings of the ICITMS, Hong Kong, China*, 93: 797–803.

Real-time individual pig tracking and behavioural metrics collection with affordable security cameras

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Abstract

This paper presents a real-time pig tracking and behavioural metrics collection system based on affordable security cameras. The proposed approach uses machine learning to detect pigs from images and automatically classify each animal's posture at any given time. This behavioural metrics collection system can be used for real-time monitoring of group or individual behaviour at the commercial and research level. Commercial applications include real-time health monitoring, reproduction decision-making, welfare assessment, and task automation, among others.

Keywords: pig tracking, pig location, sow posture analysis, pig behaviour, artificial intelligence, machine learning, behaviour metrics

Introduction

Monitoring livestock behaviour in real-time promises to open new possibilities to achieve early disease and lameness detection, better reproduction decisions and farm management, aggression and cannibalism monitoring, welfare assessment, and even more accurate environmental control, among others (Matthews *et al.*, 2016). Collecting real-time behavioural metrics in commercial farms is no simple task. A good livestock behaviour tracker would be both precise and affordable. In the last years, researchers and companies have tried different types of behaviour data acquisition systems, but the resulting solutions are still not widely adopted in the industry. Sectors in which animals have a greater value such as dairy have partially adopted accelerometer and indoor positioning systems while other sectors like swine or poultry have not been able to integrate those in their business model due to the high cost of the systems and the difficulty to implement them at a large scale. Radio Frequency Identification (RFID) has also been tried (Adrion *et al.*, 2018; Brown-Brandl *et al.*, 2016) with different species to monitor visits to some predetermined areas. Although giving interesting results, the physical implementation of such systems is complex, the equipment is invasive, and the generated data is of low resolution. In fact, RFID requires antennas at different locations and tells when an animal is detected at those positions only. Therefore, we have no information about the behaviour of the animal in between detections at the antennas.

Recent advances in artificial intelligence and specifically in computer vision open new ways to analyse livestock behaviour in a stress-free, non-invasive way. Real-time detection and multi-object tracking have reached unprecedented accuracy levels and now allow group and individual animal tracking. We propose an affordable 2D camera system to track pigs in real time and analyse biometrics. We use object (pig) detection to get individual spatial location, and individual tracking to compute velocity and acceleration. Furthermore, we use other proprietary algorithms to identify posture and group activity level, among others. This biometric data is recorded in real-time and made available through a simple user interface or analysed and used by other systems for automation and decision making. Our resulting system can be used as a research tool to better understand animal behaviour, as a diagnosis tool for veterinarians, as a data generation system to be used by decision-making algorithms, and as an affordable farm management tool to alert pig producers in

case of abnormal behaviour changes. Furthermore, the smaRt Tracking system is used as an important analytics module by multiple other Ro-Main artificial intelligence-powered tools such as smaRt Breeding, smaRt Counting, and smaRt Inventory.

Material and methods

Experimental data

The images used to assess the precision of the algorithms were collected using the Ro-Main smaRt Cam - an IP67-rated network security camera designed for use in an animal barn with infra-red night vision capabilities - and processed using the algorithms of the Ro-Main smaRt Tracking system (Conception Ro-Main inc., St-Lambert-de-Lauzon, Quebec, Canada). The camera is powered over Ethernet (PoE), collects images at a frequency up to 25 Hz, and has a focal length of 2.8 millimetres.

Images were collected in different farm environments and with different sizes of pigs to assess the robustness of the algorithms. Images were collected day and night even when all lights were off so that the algorithms were also tested in night vision mode.

Images were sampled periodically to avoid taking two very similar images. The sampling ratio – the number of randomly selected images compared to the total number of images – was chosen according to the speed at which the animals change positions or posture. The average sampling interval based on the chosen sampling ratios are approximately ten minutes for sows housed in stalls and eight seconds for pigs running in corridors.

Each image was annotated manually. Bounding boxes were drawn around each animal in the images used for testing the pig detection algorithm. The posture of the sows housed in individual stalls was classified for each stall number in all the images. The four posture classes were lying, standing, sitting and kneeling. While the definition of three first postures is obvious, the kneeling posture is defined as kneeling forward with the back legs in complete extension.

Description of the Ro-Main smaRt Tracking system

The Ro-Main smaRt Tracking system (Conception Ro-Main inc. St-Lambert-de-Lauzon, Quebec, Canada, patent pending) consists of a wide-angle IP camera network overlooking animal pens, a server that processes the images and a user interface that allows data to be visualised and to export it (Figure 1). Each wide-angle camera (2) is installed on the ceiling such that it can see all the pigs of a given pen (1) and all cameras are connected to the dedicated local area network (LAN) through Ethernet and Power over Ethernet switches (3).

A computational server (4) receives the video streams from all connected cameras and processes the individual images. Each pig is automatically detected in the image with the use of a deep neural network carefully trained to recognise pigs of all sizes and positions independently of the environment or lighting conditions. For every image, the output of the system is the XY coordinates of the centre of mass of every detected pig in the image (Figure 2). For individual tracking, frequent images are necessary to associate the subsequent detections of a same pig in the video and link them to create an individual path. The individual tracking algorithm uses a statistical approach based on prior knowledge about the animal's position and velocity to associate each detection at a time t with its most likely position at time t+1. The output of the individual tracking algorithm is a track for each pig and associated position and velocity at all data points. In parallel to the tracks, other biometric data is calculated from the video streams, such as posture and group activity levels, among others.

Finally, a local web application allows the user to access the data wirelessly from any platform (Mac, Windows, iOS, Android, Linux, etc.) through a web browser (5). The user can visualise individual and group data from the application and the raw data can be exported to standard database formats such as CSV and TXT (6).

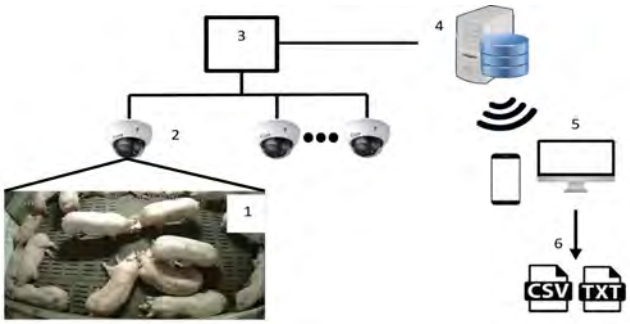

Figure 1. Ro-Main smaRt Pig Tracking system architecture

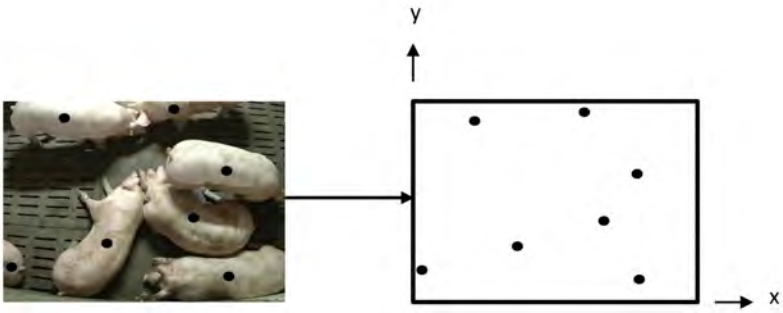

Figure 2. Output of the detection algorithm

Data analysis

The accuracy of the pig detection algorithm was based on the analysis of an evaluation metric called intersection over union (IoU). IoU is the ratio of intersection and union of a manually annotated bounding box taken as the ground truth and a predicted bounding box generated by the algorithm (Figure 3). Intersection of the two bounding boxes is measured by taking the area of overlap between the two bounding boxes, while union is measured by taking the total area covered by the two bounding boxes (Figure 4).

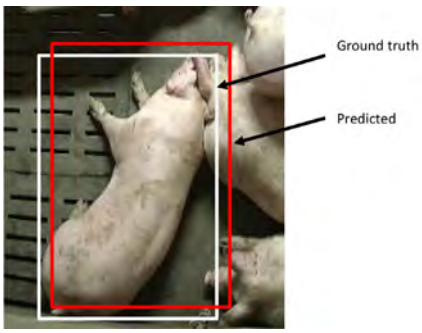

Figure 3. Output of the detection algorithm

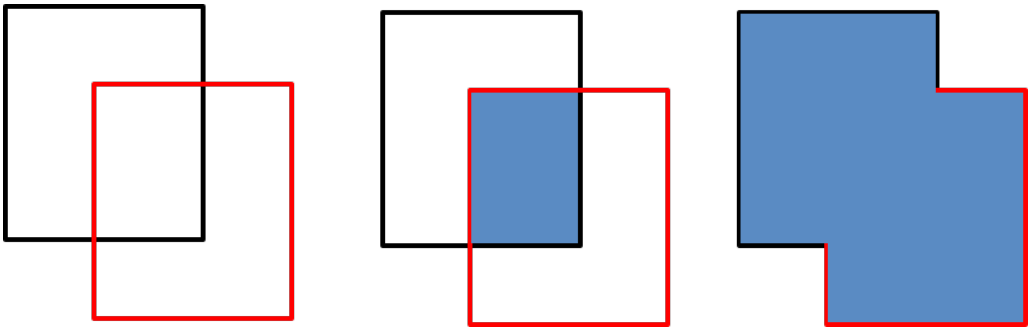

Figure 4. Intersection (centre) and union (right) of two bounding boxes (left)

The predicted bounding box was taken as correct when the IoU was above 0.7, meaning that 70% of the area covered by the two bounding boxes is shared by the two bounding boxes. A confusion matrix was then calculated from the comparisons based on IoU. Specificity and precision of our algorithm were finally calculated from the confusion matrix.

The accuracy of the posture evaluation task was done by comparing the predictions of our posture analysis algorithm on the task of classifying sows as standing, lying, sitting or kneeling with human annotations. A confusion matrix was then produced, and specificity, precision, and sensitivity of our algorithm were finally calculated from the confusion matrix.

All images used to test the algorithms were never used for designing the algorithms. Moreover, the test dataset is composed only of images taken at different locations than the images used for designing the algorithms.

Results and discussion

Pig detection

Table 1. Confusion matrix for the pig detection algorithm

	Detected by human	Not detected by human
Detected by algorithm	438	0
Not detected by algorithm	7	N/A

The algorithm was tested using 208 images with and without pigs in which human annotators identified 438 pigs. Table 1 presents the confusion matrix of the pig detection algorithm. The algorithm detected 438 pigs correctly based on an IoU of 0.7 and could not identify seven pigs that were identified by human annotators. There was no false detection from the pig detection algorithm. The true negative value of the confusion matrix is not available as the matrix is based on the positive detection of pigs. However, 14 of the analysed images had no pigs in them and the algorithm correctly arrived at that same conclusion. It is interesting to note that some images also included humans among pigs, and they were also not detected as pigs by the algorithm. Figure 5 presents an example of an image with human annotations and the same image with the predictions of our algorithm.

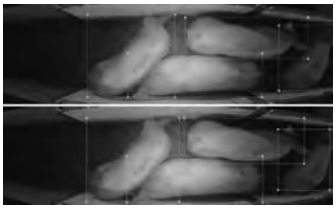

Figure 5. Comparison between human annotations (above) and algorithm predictions (below) for detecting pigs in an image

Based on the obtained confusion matrix, the sensitivity of our pig detection algorithm is 98.4% and its precision is 100%. This suggests that our algorithm can identify pigs very well in images and that this detection can be used for both group behaviour tracking and ultimately for individual behaviour tracking. Future work will aim at evaluating the precision of individual tracking.

Group behaviour analysis can be achieved without individual tracking by using only the position data provided in real time by the pig detection algorithm. This can provide valuable insights that have never been available so far at the commercial level.

With the use of our pig detection algorithm and the developed smaRt Tracking software, it is possible to know the exact number of pigs in all pens at any time and be warned when a pig has been detected at the same position for an extended period. This can be used to identify dead or sick pigs or to monitor dead animal removal and help identify the number of pigs transferred to hospital pens on a day-to-day basis. Animal positions can also be used to monitor the number of visits to pre-determined areas – set through a provided software interface - such as feeding, drinking, resting, and playing areas. Research has shown that a change in the number of visits to specific areas can be an indicator of problems (Matthews *et al.*, 2016). The system can also provide information about animal density in pre-determined zones. Animal density could be used to identify tail biting (Edwards, 2006), ventilation, and barn design issues, among others. Animal density maps can be easily plotted to visualise the general behaviour of the group with respect to its environment. This could eventually help understand ventilation and barn design problems.

Tracking each animal individually is possible using a pig detection algorithm. However, the task is much more computation intensive than simple object detection as it requires more frequent image analysis. Individual tracking has the potential to help understand better the need of individual animals. Individual behaviour monitoring could lead to earlier individual disease or lameness detection, estrus detection (Cornou, 2006), early farrowing prediction (Cornou & Lundbye-Christensen, 2012; Oczak *et al.*, 2015), or even animal interaction monitoring such as aggression and tail biting. Ro-Main's smaRt Tracking system can track animals individually given that its controller is powerful enough to process enough images in real-time. The individual tracking functionality is currently used in research only due to the higher price point. Although, somehow unaffordable at the commercial farm level for now, this system promises to get more affordable as technology evolves in the following years.

Aside from being used for research, the smaRt Tracking individual tracking algorithms are used to automate some tasks in farms. One example of this is Ro-Main's smaRt Counting system that uses individual tracking to count pigs automatically as they go through a corridor. This system uses a single camera mounted on the ceiling of a corridor and counts pigs positively if they cross the field in view of the camera in the counting direction and negatively if they cross it in the opposite direction.

Posture analysis

Figure 6. Sample image used for testing the algorithm

Figure 6 presents an example of an image that was used for testing the algorithm. This image was never used for training the model. The posture of the four sows shown in Figure 6 were correctly classified by the model (sows 1 and 4 as lying, sows 2 and 3 as standing).

Table 2. Confusion matrix for the pig posture classification algorithm

	Lying	Standing	Sitting	Kneeling
Lying predicted	9,969	324	64	72
Standing predicted	112	2,383	16	89
Sitting predicted	35	27	75	10
Kneeling predicted	7	3	1	0

The algorithm was tested using images in which four sows in individual stalls were targets for the analysis of posture. Table 2 is the confusion matrix obtained from the predictions of our algorithm. From this matrix, we can see that the algorithm correctly identified the posture of 12,427 sows and was wrong for 760 sows on a total of 13,187 sows. Table 3 shows the sensitivity, specificity, and precision for the four postures.

Table 3. Sensitivity, specificity and precision for the four postures

	Lying	Standing	Sitting	Kneeling
Sensitivity	98.5%	87.1%	48.1%	0.0%
Specificity	85.0%	97.9%	99.4%	99.9%
Precision	95.6%	91.7%	51.0%	0.0%

From Table 3, we can see that our algorithm performs well at the task of differentiating between standing and lying sows. We see that the natural imbalance of the data gives to the algorithm a natural tendency to classify more sows as lying. Future work will address this imbalance of the data to improve sensitivity for the standing posture and specificity for the lying posture. Our algorithm clearly lacks sensitivity and precision for identifying sitting and kneeling sows. In fact, these postures are very rare with 1.2% and 1.3% of occurrence for sitting and kneeling, respectively. Therefore, it is very hard to balance the training dataset for a good identification of these postures. Future work will include training the algorithm with more occurrences of these postures.

Our results suggest that our algorithm can identify very well the standing and lying postures of sows in images and that this can be used as a metric for behaviour analysis. Future work will aim at evaluating the precision of posture analysis for pigs housed in groups. Posture is an important behaviour metric that has the potential to be used in multiple ways such as predicting the onset of farrowing (Cornou *et al.*, 2011), detecting lameness, predicting piglet crushing (Mainau *et al.*, 2009), or detecting the onset of estrus. Posture – as detected from the developed algorithm – is currently used in Ro-Main's smaRt Breeding system as one of the variables used to predict the best timing for insemination based on behaviour. The resulting precision breeding system analyses time series composed by the posture of individual sows housed in stalls to predict an optimal timing for insemination.

Conclusions

Our real-time individual pig tracking and behavioural metrics collection system can generate valuable group or individual behaviour metrics that can, in turn, be used to automate tasks, raise alerts, or help pig producers make better and faster decisions. It can also help the research community to better understand pig behaviour and equipment companies to better evaluate their products with respect to animal behaviour. Moreover, it can be used by veterinarians as a diagnosis tool or by engineers as a ventilation calibration tool.

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References

Adrion, F., Kapun, A., Eckert, F., Holland, E.-M., Staiger, M., Götz, S., and Gallmann, E. (2018). Monitoring trough visits of growing finishing pigs with UHF-RFID. *Computers and Electronics in Agriculture,* 144: 144–153.

Brown-Brandl, T.M., Jones, D.D., and Eigenberg, R.A. (2016). Modelling Feeding Behaviour of Swine to Detect Illness. In: Int. Conf. Proc. (eds) *International Conference on Agricultural Engineering,* CIGR – AgEng 2016, Aarhus, Denmark, 1–6.

Edwards, S.A. (2006). Tail biting in pigs: Understanding the intractable problem. *The Veterinary Journal*, 17: 198–199.

Matthews, S.G., Miller, A.L., Clapp, J., Plotz, T. and Kyriazakis, I. (2016). Early detection of health and welfare compromises through automated detection of behavioural changes in pigs. *The Veterinary Journal*, 217: 43–51.

Cornou, C. and Lundbye-Christensen, S. (2012). Modelling of sows diurnal activity pattern and detection of parturition using acceleration measurements. *Computers and Electronics in Agriculture,* 80: 97–104.

Cornou, C. (2006). Automated oestrus detection methods in group housed sows: Review of the current methods and perspectives for development. *Livestock Science,* 105: 1–11.

Oczak, M., Maschat, K., Berckmans, D., Vranken, E. and Baumgartner, J. (2015). Classification of nest-building behaviour in non-crated farrowing sows on the basis of accelerometer data. *Biosystems Engineering,* 140: 48–58.

Cornou, C., Lundbye-Christensen, S. and Kristensen, A.R. (2011). Modelling and monitoring sows' activity types in farrowing house using acceleration data. *Computers and Electronics in Agriculture,* 76: 316–324.

Mainau, E., Dalmau, A., Ruiz-de-la-Torre, J. and Manteca, X. (2009). Validation of an automatic system to detect position changes in puerperal sows. *Applied Animal Behaviour Science,* 121: 96–102.

Developing sensor technologies to inform breeding approaches to reduce damaging behaviour in laying hens and pigs: The GroupHouseNet approach

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Abstract

The European COST Action GroupHouseNet aims to provide synergy for preventing damaging behaviour in group-housed pigs and laying hens. One area of focus of this network is how genetic and genomic tools can be used to breed animals that are less likely to develop damaging behaviour directed at their pen-mates. Reducing damaging behaviour in large groups is a challenge, because it is difficult to identify and monitor individual animals. With the current developments in sensor technologies and animal breeding, there is the possibility to identify individual animals, monitor individual behaviour, and link this information to the genotype. Using a combination of sensor technologies and genomics enables us to select against damaging behaviour in pigs and laying hens.

Keywords: damaging behaviour, genetic selection, automatic tracking

Introduction

The European COST Action GroupHouseNet (www.grouphousenet.eu) aims to provide synergy for preventing damaging behaviour in group-housed pigs and laying hens. One area of focus of this network is how genetic and genomic tools can be used to breed animals that are less likely to develop damaging behaviour directed at pen-mates. The behaviours we are focussing on are feather pecking in laying hens (Rodenburg *et al.*, 2013) and tail biting in pigs (Valros *et al.*, 2015). As both animal species are kept in groups, identifying actual performers of this behaviour (peckers and biters) at the individual level remains challenging. At the same time individual tracking is pivotal for breeding approaches. Using traditional behavioural observations is possible, but time consuming and costly. Here, we propose that a combination of sensor technologies and genomic methods should be used as a more feasible strategy to select against damaging behaviour in laying hens and pigs (Rodenburg *et al.*, 2017a). We compare different sensor technologies that can be used to identify individual animals for breeding, discuss the identification of indicator traits using data from sensor technologies, and discuss applications to animal breeding.

Sensor technology

With the current developments in sensor technologies, breeding for laying hens and pigs that show less damaging behaviour by selecting animals using sensor data might offer solutions to these welfare challenges. We propose using a combination of sensor technology and genomic methods to solve this issue (Figure 1).

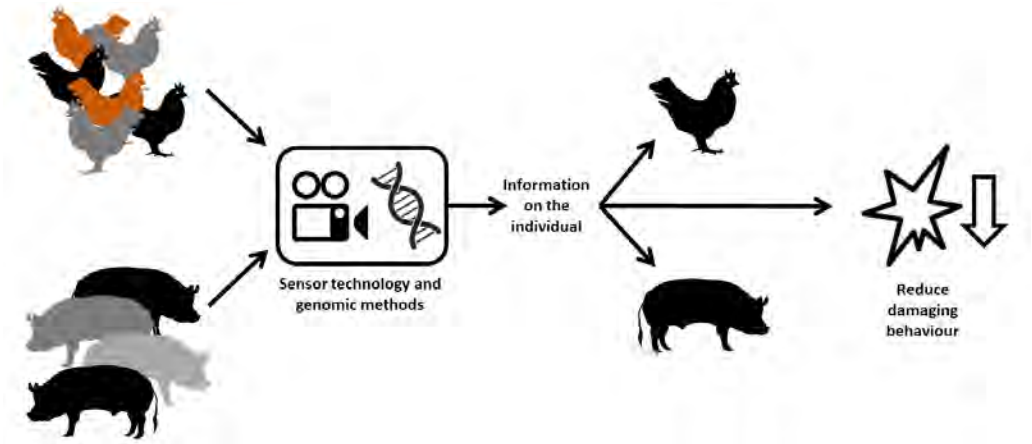

Figure 1. Overview of the approach to derive individual sensor and genomic data from group-housed pigs and laying hens and then combine this information to develop a genomic profile of individuals with the desired behavioural phenotype

We compare different sensor technologies (like ultra-wideband, RFID, computer vision) that can be used for detection of damaging behaviour or related behavioural traits (proxy measures). In laying hens, using video tracking and computer vision is challenging, given the small size of the animals and the large similarity between animals. When evaluating the sensor technologies used to this point, for laying hens RFID (Richards *et al.*, 2011) and accelerometer-based (Quwaider *et al.*, 2010) approaches seem most promising. Using UWB tracking, a specific type of RFID tracking using active tags on the animals, it was possible to distinguish feather peckers from non-feather peckers based on activity levels (Rodenburg *et al.*, 2017b). In pigs, computer vision is already used to record technical performance and there seems to be potential for expanding this approach to the recording of damaging behaviour (D'Eath *et al.*, 2018; Mittek *et al.*, 2018). Using computer vision, one of the main challenges is to link the correct identity to each individual and to maintain this link between identity and video image throughout the tracking period. Here, a combination between video tracking and passive RFID systems seems promising, as the RFID system can be used to re-assign the correct identity to individual animals. If sensor signatures and genomic fingerprints of individual animals can be combined, this would greatly improve our possibilities to reduce damaging behaviour through genetic selection.

Linking sensor information to genetic information

We are now at a point where both sensor technology and genomics approaches have the potential to provide a large amount of data at the level of the individual animal, which can be used to understand and selectively breed against damaging behaviours, such as feather pecking (FP) in laying hens. For example, the high and low FP lines (Kjaer, 2017), selected on whether they show high or low FP behaviour, have been characterised in genomic and transcriptomic studies. These studies have added to our knowledge of the mechanisms underlying FP behaviour and can also be used to record genomic profiles of individual birds. Similarly, using sensor technology, we can now record detailed information on hens from the lines, creating an individual behavioural profile, describing a hen's activity, location and proximity to other individuals (Rodenburg *et al.*, 2017b; Rufener *et al.*, 2018). If we use both sensor and genomic technological approaches in a breeding population, we can link the genomic data to the behavioural data, and define the genomic profile of individuals that show the desired behaviour (for example, low or no damaging behaviour). As a prerequisite,

however, we need to determine genetic parameters for each indicator trait derived from sensor data, especially the genetic correlations between indicator and target trait. Once thought impossible, this approach may now be feasible, because breeding companies have begun to genotype their breeding stock routinely and they are also investing in methods for automatic phenotyping. Once the desired genomic profile has been defined, we can test whether selecting for this profile will reduce damaging behaviour by breeding a next generation based on genomic selection and then phenotyping this generation with the same tools that were used to phenotype the parent stock. We feel that a combined sensor and genomics approach has great promise to select against complex behavioural traits that involve multiple individual animals in a group, such as damaging behaviour in pigs and laying hens.

Conclusions

Reducing damaging behaviour is an important goal for commercial poultry and pig production. The current developments in animal breeding and Precision Livestock Farming offer solutions to reduce damaging behaviour. We argue that a combined sensor and genomics approach has great promise to select against complex behavioural traits, especially when combining sensors like computer vision and RFID tracking.

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References

D'Eath, R.B., Jack, M., Futro, A., Talbott, D., Zhu, Q.M., Barclay, D., and Baxter, E.M. (2018). Automatic early warning of tail biting in pigs: 3D cameras can detect lowered tail posture before an outbreak. *PLoS One,* 13: 18.

Kjaer, J.B. (2017). Divergent selection on home pen locomotor activity in a chicken model: Selection program, genetic parameters and direct response on activity and body weight. *PLoS ONE*, 12, e0182103.

Mittek, M., Psota, E.T., Carlson, J.D., Pérez, L.C., Schmidt, T., and Mote, B. (2018). Tracking of group-housed pigs using multi-ellipsoid expectation maximisation. *IET Computer Vision*, 12: 121–128.

Quwaider, M.Q., Daigle, C.L., Biswas, S.K., Siegford, J.M., and Swanson, J.C. (2010). Development of a wireless body-mounted sensor to monitor location and activity of laying hens in a non-cage housing system. *Transactions of the ASABE* 53, 1705–1713.

Richards, G.J., Wilkins, L.J., Knowles, T.G., Booth, F., Toscano, M.J., Nicol, C.J., and Brown, S.N. (2011). Continuous monitoring of pop hole usage by commercially housed free-range hens throughout the production cycle. *Veterinary Record,* 169: 338-U358.

Rodenburg, T.B., van Krimpen, M.M., de Jong, I.C., de Haas, E.N., Kops, M.S., Riedstra, B.J., Nordquist, R.E., Wagenaar, J.P., Bestman, M., and Nicol, C.J. (2013). The prevention and control of feather pecking in laying hens: identifying the underlying principles. *World's Poultry Science Journal*, 69: 361–374.

Rodenburg, T.B., Bennewitz, J., de Haas, E.N., Kostal, L., Pichova, K., Piette, D., Tetens, J., van der Eijk, J.A.J., Visser, B., and Ellen, E.D. (2017a). The use of sensor technology and genomics to breed for laying hens that show less damaging behaviour. In: Berckmans, D., Keita, A. (Eds.), *Precision Livestock Farming '17*, Nantes, France, pp. 532–541.

Rodenburg, T.B., van der Eijk, J.A.J., van Mil, B., Pichova, K., and de Haas, E.N. (2017b). PhenoLab: automatic recording of location, activity and proximity in group-housed laying hens. In: Berckmans, D., Keita, A. (Eds.), *Precision Livestock Farming '17*, Nantes, France, pp. 269–275.

Rufener, C., Berezowski, J., Maximiano Sousa, F., Abreu, Y., Asher, L., and Toscano, M.J. (2018). Finding hens in a haystack: Consistency of movement patterns within and across individual laying hens maintained in large groups. *Scientific Reports* 8, 12303.

Valros, A., Palander, P., Heinonen, M., Munsterhjelm, C., Brunberg, E., Keeling, L., and Piepponen, P. (2015). Evidence for a link between tail biting and central monoamine metabolism in pigs (Sus scrofa domestica). *Physiology & Behavior,* 143: 151–157.

Defining resilient pigs after a Porcine Reproductive and Respiratory Syndrome Virus (PRRSV) challenge using activity and feeding data from accelerometers

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Abstract

Porcine reproductive and respiratory syndrome (PRRS) is an infectious viral disease in pigs. PRRS causes reproductive failure in sows and respiratory infections in growing pigs. To improve pig health and minimise economic losses, resilient pigs are preferred within the herd. Resilient pigs still become infected, yet are able to recover following infection, showing less variation in activity and feeding. In this study, 232 commercial crossbred pigs were equipped with individual accelerometer ear tags to monitor the number of active, feeding, and hyperactive events per individual per hour. At eight weeks of age, pigs were inoculated with PRRS virus 1-7-4. Data from accelerometers were collected 23 days prior to challenge and 42 days post-infection (dpi). Expected levels of activity, feeding, and hyperactivity were estimated by regressing behavioural traits on observed datapoints prior to challenge. This regression line was extended to 42 dpi. Then, deviations from the regression line were quantified as Root Mean Square Error (RMSE) for each individual during the following time periods: pre-challenge, 0–13 dpi, and 13–42 dpi. All traits decreased and RMSE increased post-challenge. These results are consistant with clinical signs of PRRS, including lethargy and loss of appetite. In addition, association of these traits with survival was also investigated. RMSE prior to PRRS-infection was not predictive of survival after infection. However, RMSE of feeding and activity during the peak challenge period (0–13 dpi) was predictive of survival, where pigs with less deviation in behaviour were more resilient to the PRRS challenge.

Keywords: PRRS, accelerometers, RMSE, resilience, behaviour, pig

Introduction

Porcine reproductive and respiratory syndrome (PRRS) is an infectious viral disease and is present in almost every major pork producing country (Dea *et al.*, 2000). It emerged in North America around 1989 (Collins *et al.*, 1991) and in Europe three years later (Wensvoort *et al.*, 1991). Mortality rates up to 20% due to North American strains and up to 10% due to European strains has been observed (Lunney *et al.*, 2010). As its name implies, PRRS results in two main pathologies: reproductive failure and respiratory disease. Reproductive failure occurs in pregnant sows and results in abortions, mummified piglets, and weak live born piglets. Growing pigs infected with PRRS may suffer from high fever, loss of appetite, and become lethargic or less active. This could also lead to reduced growth and productivity. The course of the clinical signs is on average two weeks. Besides the impairment of pig welfare, PRRS causes severe economic losses to the farmer, estimated at $74.16 per litter and $7.67 per finisher (Neumann *et al.*, 2005). To improve pig health and curtail economic losses, resilient pigs are preferred within the herd. Resilient pigs are able to recover relatively quickly, and actively lower the viral load within the herd in spite of being infected (Berghof *et al.*, 2018).

Implementing selection for pigs with increased resilience to PRRSV-infection would be desirable for a breeding program. However, resilient breeding candidates are difficult to identify. One approach that can be used to quantify resilience is to compare normal expectations to behaviour following a disease challenge. Each animal has a unique pattern of behaviour, and deviations from this pattern following disease challenge, might provide insight regarding the impact of disease and/or recovery post-infection. Using human observations to measure behaviour is subjective and labour intensive. Precision phenotyping tools, such as wearbale accelerometers, which are capable of quantifying behaviour automatically are, therefore, an attractive alternative. An accelerometer measures acceleration in three dimensions. A machine learning model is then used to recognise activity, feeding and hyperactivity in the acceleration data. It has been reported that deviations from normal expectations in the activities due to disease can be used as a measure of resilience. Putz *et al.* (2018) quantified resilience using Root Mean Square Error (RMSE) of feed intake and feeding duration. It was shown that RMSE can be used as an indicator trait for resilience and quantifies return to baseline. Therefore, the objective of this study is to evaluate the usefulness of variation in activity, feeding and hyperactivity measured through accelerometers to define resilience to PRRS-infection.

Material and methods

Animals and housing

A total of 2186 commercial crossbred pigs were farrowed at a commercial sow farm and shipped to a commercial research facility at weaning. Upon arrival, pigs were balanced by sex with 27 pigs housed per pen in 81 total pens. All pigs were vaccinated per label with a PRRSV modified live virus vaccine (IngelVac ATP, Boehringer Ingelheim) upon entry and experimentally inoculated with PRRS virus variant 1-7-4 four weeks later at a total dose of 1x105 TCID50 via the IM route. Pigs received mass treatments at 21 and 26 dpi and individual treatments as needed from 21 dpi onward.

Data collection

A subset of 232 pigs was equipped with individual accelerometer ear tags from Remote Insights. Acceleration data were recorded 23 days prior to infection and 42 days post-infection (dpi). Accelerometers detected acceleration in three dimensions. A machine learning model was trained from video observations to recognise activity and chewing behaviour. Hyperactivity was calculated directly from the raw acceleration data. A hyperactive event was recorded when the acceleration surpassed a defined threshold. Activity, feeding, and hyperactivity were averaged per day and expressed in minutes per hour.

Statistical analyses

RMSE was computed for each pig by calculating the within animal variation for activity, feeding, and hyperactivity from the linear regression using R (Figure 1). Activity, feeding, or hyperactivity was regressed using only observations pre-challenge (-23 – 0 dpi). This regression line was extended to 42 dpi, obtaining expected behaviour over time without the interruption of a challenge. RMSE was calculated for each trait using the observed values from the accelerometers, and expected values from regression. The following formula was used to calculate RMSE for each period:

$$RMSE = \sqrt{\frac{\sum(Observed - Expected)^2}{Number\ of\ observations}} \qquad (1)$$

Where *Observed* is the observed value from the accelerometer, *Expected* the expected value based on the linear regression. RMSE was calculated pre-challenge (-23 – 0 dpi), early post-

infection (0–13 dpi) and late post-infection (13–42 dpi). Data were analysed using a linear mixed model in ASReml. Sex was fitted as a fixed effect and pen was fitted as a random effect.

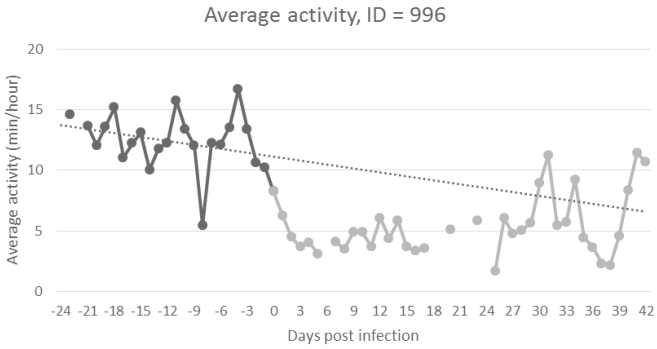

Figure 1. Example of activity data per day in minutes per hour generated by the accelerometer. The dots are observed activity, where the darker shade of grey is used for the linear regression. The solid line represents the time of PRRS infection and the dashed line the linear regression of expected activity and arrows show examples of deviations from expectations

Results and discussion

Behaviour

Table 1 shows average activity, feeding, and hyperactivity for each period in minutes per hour. The pigs were less active and spent less time feeding post-challenge compared to pre-challenge. Hyperactivity was not affected by PRRS-infection to the same extent as activity and feeding. Activity, feeding, and hyperactivity did not return to baseline post-challenge. Nordgreen *et al.* (2018) observed similar behaviour, where individuals were less active and had less appetite post-challenge than pre-challenge. These results show that accelerometer data reflect the expected change in behaviour due to PRRS-infection.

Table 1. Difference in average activity, feeding, and hyperactivity in minutes per hour for different periods for pigs who were either dead or alive at the end of the challenge

Average	Activity (min/h)		Feeding (min/h)		Hyperactivity (min/h)	
	Alive	Dead	Alive	Dead	Alive	Dead
Pre-challenge	12.53	12.34	6.33	6.08	0.36	0.43
Early post-challenge	8.05	5.85	3.89	2.19	0.30	0.29
Late post-challenge	7.05	5.22	4.03	1.91	0.27	0.30

A linear regression was fitted on data pre-challenge to estimate the expected behavioural pattern of a pig over time. As anticipated, pigs deviated from this expected patten following challenge, reflected by increased RMSE values for each trait: activity, feeding, and hyperactivity. Of these traits, activity had the highest RMSE, regardless of time period (Figure 2). Of the time periods, the late post-challenge period (13–42 dpi) had the highest RMSE, regardless of trait. Based on Table 1 we can conclude that the increase in RMSE is due to a decrease in activity, feeding, and hyperactivity following disease challenge, which is consistent with clinical signs of PRRS-infection, including lethargy and loss of appetite.

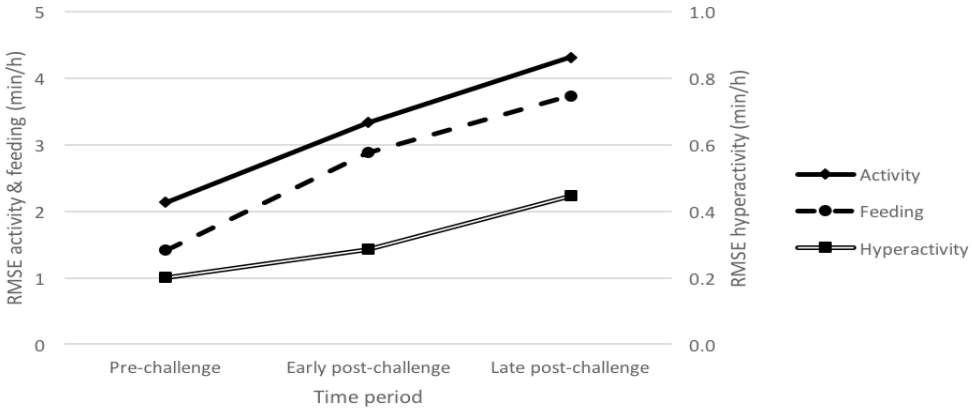

Figure 2. Average RMSE for activity, feeding, and hyperactivity for each period

Survival

Resilience to PRRS-infection was also assessed using survival data. Compared to pigs that died following infection, pigs that survived had lower RMSE for activity and feeding from 0–13 dpi, and lower RMSE for activity and hyperactivity from 13–42 dpi (Table 2). These results suggest that it is possible to identify pigs that will survive the challenge based on RMSE for activity and feeding shortly after challenge. Although it would be more desirable to identify resilient pigs without the need of a PRRS-infection, the lack of a significant effect of RMSE pre-challenge on survival suggests that variation in behaviour in the absence of disease did not truly reflect the chances of survival following infection.

Table 2. Solutions of RMSE early and late post-challenge of activity, feeding, and hyperactivity of animals that survived PRRS-infection compared to deceased pigs. NS = non-significant

Solution RMSE	Activity	Feeding	Hyperactivity
Early post-challenge	-1.48 ± 0.35	-1.57 ± 0.36	NS
Late post-challenge	-2.41 ± 0.81	NS	-0.15 ± 0.07

Conclusions

Results from this study suggest that accelerometer data can be used to characterise the behavioural patterns of pigs. Activity, feeding, and hyperactivity decreased post-challenge, which is consistent with the classical signs of PRRS-infection. Prolonged infection was observed, since neither activity, feeding, nor hyperactivity returned to baseline by 42 dpi, which suggests that pigs had not yet recovered from the infection by this timepoint. RMSE was used to quantify the deviation of a pig's observed behaviour post-infection from its expected behaviour. Results showed that RMSE of activity, feeding, and hyperactivity prior to PRRS-infection were not predictive of survival. However, RMSE during the early post-infection phase (0–13 dpi) was predictive of survival, where pigs with lower RMSE for activity and feeding during this phase were more resilient to PRRS challenge.

References

Berghof, T.V., Poppe, M., & Mulder, H.A. (2018). Opportunities to Improve Resilience in Animal Breeding Programs. *Frontiers in genetics, 9*.

Collins, J.E., Benfield, D., Christianson, W., Harris, L., Gorcyca, D., Chladec, D., & Morrison, R. (1991). *Swine infertility and respiratory syndrome (mystery swine disease)*. Paper presented at the Proc MN Swine Conf for Vets.

Dea, S., Gagnon, C., Mardassi, H., Pirzadeh, B., & Rogan, D. (2000). Current knowledge on the structural proteins of porcine reproductive and respiratory syndrome (PRRS) virus: comparison of the North American and European isolates. *Archives of Virology, 145*(4): 659–688.

Neumann, E.J., Kliebenstein, J.B., Johnson, C.D., Mabry, J.W., Bush, E.J., Seitzinger, A.H., . . . Zimmerman, J.J. (2005). Assessment of the economic impact of porcine reproductive and respiratory syndrome on swine production in the United States. *Journal of the American Veterinary Medical Association, 227*(3): 385–392.

Nordgreen, J., Munsterhjelm, C., Aae, F., Popova, A., Boysen, P., Ranheim, B., . . . Lervik, A. (2018). The effect of lipopolysaccharide (LPS) on inflammatory markers in blood and brain and on behavior in individually-housed pigs. *Physiology & Behavior, 195*: 98–111.

Putz, A.M., Harding, J.C., Dyck, M.K., Fortin, F., Plastow, G.S., Dekkers, J.C., & Canada, P. (2018). Novel resilience phenotypes using feed intake data from a natural disease challenge model in wean-to-finish pigs. *Frontiers in Genetics, 9*.

Wensvoort, G., Terpstra, C., Pol, J., Ter Laak, E., Bloemraad, M., De Kluyver, E., . . . Wagenaar, F. (1991). Mystery swine disease in The Netherlands: the isolation of Lelystad virus. *Veterinary Quarterly, 13*(3): 121–130.

Comparison of architectures and training strategies for convolutional neural networks intended for location-specific counting of slaughter pigs

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Abstract

Pen fouling is an undesired behaviour seen in growing pigs, where they start resting in the excretion area and excrete in the designated resting area. It is reasonable to assume that automatic monitoring of the location of the pigs within the pen could be used for early warnings of imminent pen fouling events. We intend to provide such automatic monitoring using convolutional neural networks (CNN) applied to images captured above the pens. In this preliminary study, we compared 12 different combinations of CNN architectures and training strategies for this purpose. The best performing strategy yielded an overall mean absolute error of 0.35 pigs and a coefficient of determination of 96% between the predicted and observed number of pigs in a given area of the pen.

Key words: Convolutional neural network, fouling, monitoring, slaughter pig

Introduction

Pen fouling is an undesired behaviour sometimes seen in pigs, where they will start to excrete in the resting area of the pen and rest in the designated excretion area of the pen. This behaviour has several consequences such as higher labour cost, poorer hygiene (Rantzer *et al.*, 1999), and higher ammonia emissions (Aarnink *et al.*, 1997). It would be beneficial to be able to predict fouling in order to take pre-emptive action against it. Pen fouling is obviously closely connected with lying behaviour (Aarnink *et al.*, 2006; Huynh *et al.*, 2005), and a recent study suggests that changes in lying behaviour actually occur a few days prior to the onset of pen fouling (Larsen *et al.*, 2018).

The long-term goal of our research is to be able to predict fouling by automatically monitoring the positioning behaviour of the finisher pigs, which we intend to accomplish by means of convolutional neural networks (CNN) applied to images captured above finisher pig pens. CNNs are commonly used for image classification tasks, such as face recognition of humans (Taigman *et al.*, 2014) or pigs (Saint-Dizier & Chastant-Maillard, 2012). In addition to categorical outputs, CNNs can also be designed to yield linear outputs, such as, e.g. predicted live weight of a pig in an image (Jensen *et al.*, 2018; Wang *et al.*, 2008). For this research, we are using CNNs with linear outputs to count pigs in a given image of a subsection of a pen.

Our aim with this preliminary study is to determine the optimal combination of CNN architecture and training strategy to best count the number of pigs in a given image.

Materials and methods

Data source and handling

The data used in this study were collected at the Aarhus University, Denmark experimental farm. The data were collected from three pens during one finisher pig period of 69 days. Each of these three pens can be seen in Figure 1. The images were cropped to minimise the visible areas of neighbouring pens, and Figure 1 shows this cropping. Pen a (Figure 1a) was provided with straw during the entire growth period, while pens b and c (Figures 1b

and 1c, respectively) were not. Two wooden beams were positioned in separate vertical racks as enrichment to ensure that all pens were in accordance with the legislation (EU Council Directive 2008/120/EC). Each of the pens used in this study held 11 pigs at the time of insertion (1.21 m^2/pig). The pens measured 2.48 m × 5.45 m. Artificial light was on from 05:30–18:30 h (182 lx) in the room. Windows in the room were blocked due to video recordings. The room temperature was controlled by an automatic ventilation system (SKOV A/S, Roslev, DK). The climate control system automatically controlled a shower system above the slatted floor.

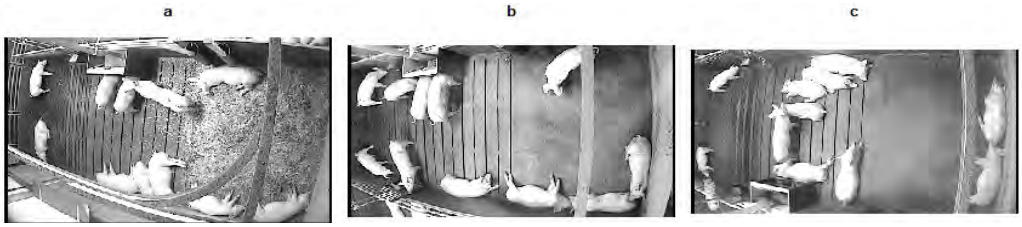

Figure 1. Cropped images of the pens from which data were used for this study. Pens a and b were used for training the convolutional neural networks to count the number of pigs in each area of the pens, while pen c was used for testing the trained networks

The floor was made of concrete and was divided between 1/3 solid, 1/3 drained and 1/3 slatted. The solid area served as the pigs' resting area, while the slatted floor was the pigs' designated excretion area. A camera was placed above the solid floor of the pens, and angled so that the entire pen was visible to the camera. Continuous video data were recorded for each pen for the entire growth period with a resolution of 768 × 576 pixels. From the continuous video data, still-images were extracted with 10 minute intervals for two 2-hour periods per day from 06:00–08:00 hours (morning data) and from 12:00–14:00 hours (afternoon data), producing a total of 26 images per pen per day for the entire growth period. For each of these images, it was manually recorded how many pigs were in each of the three areas of the pen. If a given pig was partially in two different areas in the same image, the area with the largest portion of the pig was counted. In cases where the pig was evenly divided between two areas, the area with the pig's head was counted. This manual recording was performed by one student worker.

Each cropped whole-pen image (top of Figure 2) extracted from the video was divided into sub-images, corresponding the three areas of the pen. These sub-images were then re-scaled to a resolution of 64 × 64 pixels, as illustrated in the bottom of Figure 4. The data relating to pens a and b were used for training the CNNs, while the data relating to pen c served as the test set. The training data were augmented using the flip-flop method, where each of the sub-images was flipped horizontally, vertically, and both horizontally and vertically, so that each sub-image gave rise to a total of four different images. This data augmentation was not applied to the test set, thus, the final training set consisted of 41,136 sub-images, while the test set consisted of 5,381 sub-images.

Modelling

The CNNs were defined and trained in R (R Core Team, 2017) using the *mxnet* package (Chen *et al.*, 2015). The CNNs were trained with the flip-flop augmented and re-sized sub-images as the input, and the numerical value of the manually counted number of pigs located in each sub-image as the target values.

Two base-architectures, A and B, were implemented. The inspiration for the architectures came mainly from an architecture originally designed for face recognition of pigs (Hansen

et al., 2018). The complexity of our networks was, however, somewhat reduced compared to this architecture. Both of our architectures had three convolutional layers and three fully connected layers. They were identical, except that a dropout rate of 50% was used after all fully connected hidden layers in architecture B, as was done by Hansen *et al.* (2018), while no dropout was used in architecture A. Furthermore, Hansen *et al.* (2018) used dropout after every other convolutional layer, but this was not used in our implementation. Each of the convolutional layers was followed by max-pooling and made use of the ReLU (rectified linear unit) activation function. All convolutional layers in our implementations used kernels of 5 × 5 pixels, with 32, 64, and 128 kernels in the first, second, and third convolutional layer, respectively. The first fully connected layer had 1,000 hidden nodes, while the second had 500 hidden nodes. Both the first and second fully connected layer used the ReLU activation function. The third fully connected layer, i.e. the output layer, had one node and used the linear activation function.

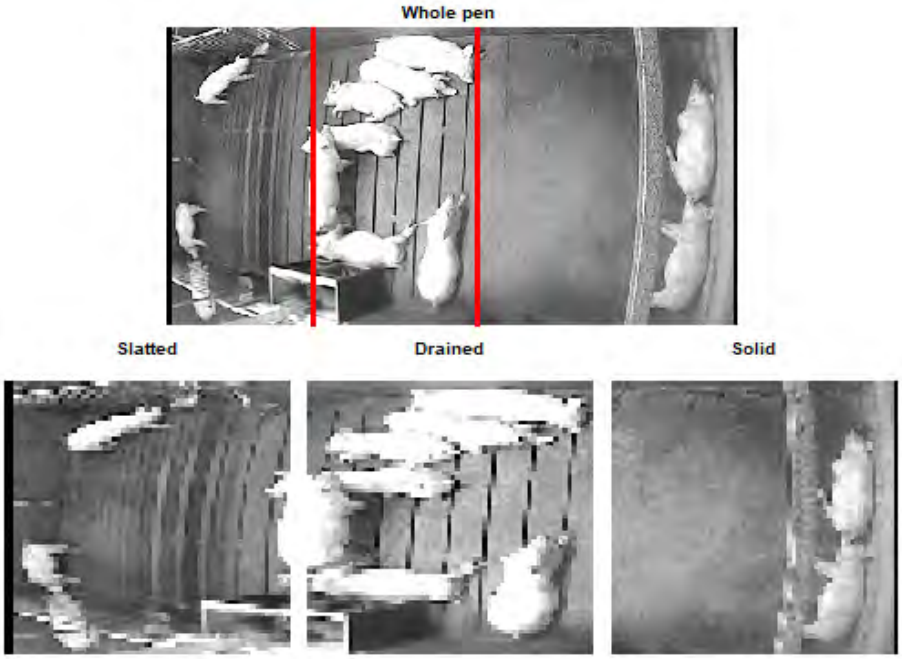

Figure 2. Top: a whole pen with 11 pigs. The two red lines mark the separations between the three different areas (left to right: slatted floor, drained floor, and solid floor). Here the slatted floor has two pigs, the drained floor has seven pigs, and the solid floor has two pigs. Any visible pig from the neighbouring pens are not counted. Bottom: the image of the whole pen is divided into three sub-images, corresponding to each of the areas in the pen. The sub-images have been re-scaled to a resolution of 64 × 64 pixels

For each of the two architectures, we compared the effects of training a separate CNN to count the pigs in each of the three areas of the pen with the effects of training a single CNN for all three areas. Furthermore, three different criteria for stopping the training was tested, namely that the root of the mean of the squared errors (RMSE) of the predicted values on the training set should be below 1.0, 0.75, and 0.5 pigs. Thus, we tested a total of 12 combinations of strategies. The time it took to train the CNNs, given the various strategy combinations, was recorded during training.

Testing

The trained CNNs were applied to the test data images. The per-image observations and predictions were aggregated to daily per-period (morning or afternoon) means, as was done with the manually counted pig location data used in a recent study (Larsen *et al.*, 2018). The prediction error was defined as seen in eq. 1.

$$e_i = Yi - \hat{Y}_i \tag{1}$$

with $\hat{Y}_i$ being the aggregated number of observed pigs during observation period

i and $\hat{Y}_i$ being the aggregated predicted number of pigs during observation period i. The mean absolute error was then calculated as follows:

$$MAE = \frac{1}{N}\sum_{i}^{N} |e_i| \tag{2}$$

where N is the total number of aggregated observations, i.e. two aggregated observations per day for 69 days, totaling 138 observations in our aggregated test set.

Results and discussion

Table 1 shows the performance measures of the 12 CNN strategy-combinations. All of the final CNNs yield aggregated pig counts, which are on average less than one pig off, compared to the aggregated manual counts.

The single best strategy was achieved by using dropout in the CNN architecture, by training a separate CNN for each of the three areas of the pen, and by stopping the training when the RMSE on the training set was below 0.5 pigs.

When separate area-specific CNNs were not used, the best performances were consistently achieved with the highest included stop value (RMSE = 1 pig); conversely, when separate CNNs were trained and applied only on specific areas within the pen, the best performance was consistently achieved with the lowest included stop value (RMSE = 0.5 pig). This suggests that overfitting is less of a problem when the final CNNs are applied to the uniform patterns of a single specific area of the pen. The best area-specific CNNs were, however, not much better than the best area-general CNNs, and the total training time to achieve these best performances were increased by 529% and 1,073% for architecture A and B, respectively, when training the area-specific rather than the area-general CNNs.

Using dropout in the fully connected layers generally increased the training time. This increase was by 54% on average. The use of dropout, however, only resulted in improved performance in two out of six cases, when keeping all other variables constant. For our purpose, the use of dropout does not seem worth the extra training time.

The best CNN took 434 minutes to train. Interestingly, the second best performance (MAE = 0.68) could be achieved in as little as 37 minutes, by training a single CNN for all areas of the pen, and ending the training when the RMSE on the training set was less than one pig. For future work, which will include larger data sets, the faster strategy might be preferable. For this study, however, all of the following discussion will relate to the strategy, which was found to yield the best performance according to Table 1.

Table 1. The performance, in terms of mean absolute error (MAE), of the CNNs achieved with the 12 different strategy-combinations, when applied to the test set. The best performance within each Architecture/Separate models-combination is highlighted with boldface. The best performance overall is highlighted with boldface and italics

Architecture[a]	Separate models[b]	Stop value[c]	MAE	Training time[d], minutes
A	No	1.00	***0.69***	38
		0.75	0.75	74
		0.50	0.75	237
	Yes	1.00	0.91	45
		0.75	0.70	85
		0.50	***0.68***	239
B	No	1.00	***0.68***	37
		0.75	0.91	109
		0.50	0.75	468
	Yes	1.00	0.68	63
		0.75	0.86	134
		0.50	0.59	434

[a]A = architecture without dropout, B = architecture with dropout; [b]Yes = a separate CNN was trained for each of the 3 areas of the pen, No = a single CNN was trained on sub-images for all areas of the pen; [c]The RMSE value of the CNN applied to the training set, which would stop the training of a given CNN; [d]The number of minutes it took before the stop value was reached during training

Table 2 shows the performances specific to each of the three areas of the pen. The uncorrected mean errors (ME) and MAE relate to the predictions from the CNN as taken at face value. As is seen, the performance specific to the solid floor is by far the worst (MAE = 1.14 pig), and the number of pigs in this area tend to be under-estimated, as is seen by the positive value of the ME. From the top row of Figure 3 it is seen that this tendency to under-estimate the number of pigs on the solid floor is greater in the morning, when more pigs are usually located in this area. This suggests that when the concentration of pigs in one area becomes too high, the CNN has difficulties with separating close pigs from each other. Inspired by this, we decided to implement a set of simple rules to correct the aggregated estimate of the number of pigs in a given area during a given period. These rules were: 1) The predicted numbers of pigs per area must sum the known total number of pigs in the pen. 2) The area of the pen, for which the uncorrected prediction is highest, is the area for which the prediction will be corrected.

Table 2. The area-specific mean errors (MA) and mean absolute errors (MAE) of the single best CNN strategy, according to Table 1, when the predicted number of pigs are uncorrected vs corrected to sum to 11

Pen area	N	Median no. of pigs	Range of pigs	Uncorrected		Corrected	
				ME	MAE	ME	MAE
Slatted	138	1	0-5	0.16	0.19	0.18	0.21
Drained	138	3	1-7	0.19	0.43	-0.01	0.38
Solid	138	7	2-9	0.65	1.14	-0.17	0.46
All	414	3	0-9	0.34	0.59	0.00	0.35

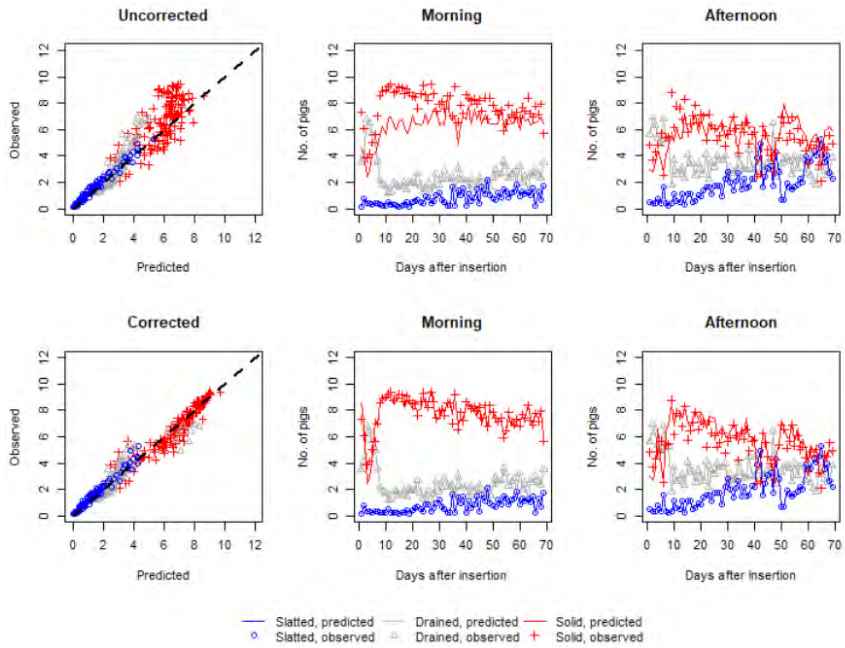

Figure 3. Top row: the CNN-based predictions of the number of pigs in each area were taken at face value. Bottom row: the CNN-based predictions were corrected, so that the number of pigs in all areas of the pen at a given point in time must always sum to the known total number of pigs in the pen. Column 1: The relationship between the observed number of pigs and the number predicted by the best area-specific CNN without and with correction. Columns 2 and 3: Time series of the observed and predicted number of pigs on the slatted, drained, and solid floor of the test set, without and with correction

From Table 2 it is seen that this correction drastically reduced both the ME and MAE for the solid floor and, to a lesser extent, the drained floor. This improvement is also clearly seen by comparing the plots in the top row of Figure 3 (uncorrected predictions) to the plots in the bottom row of Figure 3 (corrected predictions). The coefficient of determination (r^2) between all observed values and uncorrected predictions is 91%, while the r^2 between the observed values and corrected predictions is 96%.

From Figure 3 it is seen that the predicted values generally follow the pattern of the observed values over time. This demonstrates that the CNN can be used to monitor the positioning

behaviour of the pigs throughout the growth period. Furthermore, the CNN could potentially be applied continuously throughout the day, as opposed to just during two specific periods per day as was done for this study. Such continuous positioning data, aggregated to e.g. hourly means, could then be used to identify diurnal positioning patterns. By using e.g. a dynamic linear model (DLM), specific diurnal patterns could be learnt for specific groups of pigs, and deviations from the group-specific expected pattern could then be used to raise alarms of changing behaviour, which if left unchecked would lead to pen fouling. Such DLM-based alarm systems have previously been demonstrated with e.g. the diurnal patterns of drinking behaviour in finisher pigs, where deviations from the expected patterns could be used to predict diarrhoea and pen fouling (Dominiak *et al.*, 2018; Jensen *et al.*, 2017). Furthermore, the CNN-based time series of the pigs positioning behaviour could be combined with other sensor data, such as data on drinking behaviour and temperature, using a multivariate DLM. Previous studies have suggested that combining data from multiple sources in this way results in more accurate predictions of undesired events, such as diarrhoea and pen fouling in slaughter pigs (Jensen *et al.*, 2017) and mastitis in dairy cows (Jensen *et al.*, 2016).

Further studies will focus on investigating the utility of utilising the CNN-based monitoring of slaughter pig positioning behaviour in the ways described above. We will also work to improve the CNNs ability to predict the number of pigs in high-density areas by using input images with higher resolution than what was used here. This will be necessary before the CNN can be useful in commercial pig herds, where the stocking density can be expected to be considerably higher than the density used in our study.

Conclusion

We have demonstrated that CNNs can be used to count the number of pigs in different areas within the pen in a way that allows reliable long-term monitoring of the pigs' positioning behaviour. We compared 12 different combinations of CNN architectures and training strategies. On its own, the best strategy yielded an overall MAE of 0.59 pig and a r^2 of 91% between the observed and predicted number of pigs in a given area of the pen. By implementing the rules that the total number of predicted pigs always had to be equal to the known total number of pigs in the pen, and that the highest predicted count would always be corrected to achieve this sum, these performance values were boosted to a MAE of 0.35 pig and a r^2 of 96%. This method has the potential to be used as part of an early warning system for pen fouling.

Acknowledgements

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References

Aarnink, A.J.A., Schrama, J.W., Heetkamp, M.J.W., Stefanowska, J., Huynh, T.T.T. (2006). Temperature and body weight affect fouling of pig pens. *J. Anim. Sci.*, 84: 2224–2231.

Aarnink, A.J.A., Swierstra, D., van den Berg, A.J., Speelman, L. (1997). Effect of Type of Slatted Floor and Degree of Fouling of Solid Floor on Ammonia Emission Rates from Fattening Piggeries. *J. Agric. Eng. Res.*, 66: 93–102.

Chen, T., Li, M., Li, Y., Lin, M., Wang, N., Wang, M., Xiao, T., Xu, B., Zhang, C., Zhang, Z. (2015). MXNet: A Flexible and Efficient Machine Learning Library for Heterogeneous Distributed Systems. arXiv Prepr. 1–6. https://doi.org/10.1145/2532637.

Dominiak, K.N., Pedersen, L.J., Kristensen, A.R. (2018). Spatial modeling of pigs' drinking patterns as an alarm reducing method I. Developing a multivariate dynamic linear model. *Comput. Electron. Agric*. 1–13.

Hansen, M.F., Smith, M.L., Smith, L.N., Salter, M.G., Baxter, E.M., Farish, M., Grieve, B. (2018). Towards on-farm pig face recognition using convolutional neural networks. *Comput. Ind*. 98, 145–.

Huynh, T.T.T., Aarnink, A.J.A., Gerrits, W.J.J., Heetkamp, M.J.H., Canh, T.T., Spoolder, H.A.M., Kemp, B., Verstegen, M.W.A. (2005). Thermal behaviour of growing pigs in response to high temperature and humidity. *Appl. Anim. Behav. Sci.,* 91: 1–16.

Jensen, D.B., Dominiak, K.N., Pedersen, L.J. (2018). Automatic estimation of slaughter pig live weight using convolutional neural networks, in: II International Conference on Agro BigData and Decision Support Systems in Agriculture.

Jensen, D.B., Hogeveen, H., De Vries, A. (2016). Bayesian integration of sensor information and a multivariate dynamic linear model for prediction of dairy cow mastitis. *Journal of Dairy Science*, 99: 1–18.

Jensen, D.B., Toft, N., Kristensen, A.R. (2017). A multivariate dynamic linear model for early warnings of diarrhea and pen fouling in slaughter pigs. Comput. Electron. Agric., 135: 51–62.

Larsen, M.L.V., Bertelsen, M., Pedersen, L.J. (2018). Pen fouling in finisher pigs: Changes in the lying pattern and pen temperature prior to fouling. Submitted Publication.

R Core Team, (2017). R: A language and environment for statistical computing.

Rantzer, D., Westroem, B., Svendsen, J. (1999). Effects of pen hygiene and moving the pigs at weaning on pig production and health during the first 8 weeks. Rapp. - Sveriges Lantbruksuniversitet, Institutionen foer Jordbrukets Biosyst. och Teknol.

Saint-Dizier, M., Chastant-Maillard, S. (2012). Towards an Automated Detection of Oestrus in Dairy Cattle. *Reprod. Domest. Anim*., 47: 1056–1061.

Taigman, Y., Ranzato, M.A., Aviv, T., Wolf, L., Park, M. (2014). DeepFace : Closing the Gap to Human-Level Performance in Face Verification. 2014 IEEE Conf. Comput. Vis. Pattern Recognit. 1701–1708.

Wang, Y., Yang, W., Winter, P., Walker, L. (2008). Walk-through weighing of pigs using machine vision and an artificial neural network. *Biosyst. Eng.,* 100: 117–125.

Validation of the localisation accuracy of the SMARTBOW ear tag in a pasture based milking system

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Abstract

Tracking animal movements while at pasture may improve the understanding of grazing behaviour and aid farmers to locate animals in need of attention more efficiently. The SMARTBOW (Smartbow Gmbh, Weibern, Austria) system facilities the localisation of animals through triangulation from a set of receivers distributed around a farm and ear tags worn by each cow. The objective of the current study was to test the localisation accuracy of the SMARTBOW system. A total of 318 SMARTBOW tags were evenly distributed across a Teagasc research farm and left in a stationary position for approximately 10 minutes. A Leica Viva CS15 GNNS Controller in combination with a GS 608 plus Smart Antenna recorded the true location of each tag. The distance between the location calculated by the SMARTBOW system and the true location (the Euclidean distance) was derived and results showed that 2.8% of the data had a Euclidean distance greater than 3 m. The maximum Euclidean distance observed during the experiment was 235 m. The mean absolute error was 0.67 m, the one sided 95% confidence interval of the Euclidean distance was 2.75 m and the 99% confidence interval was 4.93 m.

Keywords: localisation, dairy cows, ear tag, pasture

Introduction

Localisation of animals in a pasture based system could aid in the understanding of animal grazing behaviour and where animals tend to graze and aggregate within a field. It could also help in monitoring cow flow to the milking unit when automated milking is integrated with pasture grazing. Additionally, if paired with health or calving sensors in large expansive farms, localisation technology would allow a farmer to locate animals in need of attention without delay. Previous research efforts into cow localisation have used Global Positioning System (GPS) devices. The location of a GPS device is calculated by identifying the time it takes a radio wave signal to go between the ground-based receiver and a number of carefully monitored satellites orbiting the earth. Therefore, the accuracy of the clock on the satellites is of utmost importance (Turner *et al.,* 2000). Under normal circumstances the accuracy of GPS units attached to animals have been within 0.36 m when the animal is walking (Ganskopp and Johnson, 2007). When stationary, the GPS location can drift, as Ganskopp and Johnson (2007) observed that 90% of the data fell within 5.5 m of the true location.

Alternative methods for localisation include wireless sensor networks (WSN) (Mao *et al.,* 2007). In the past, the difference between the true location and the WSN calculated location has ranged from 5–43 m (Huircán *et al.,* 2010). The SMARTBOW system (Smartbow Gmbh, Weibern, Austria) that was tested as part of the current study is a WSN consisting of multiple fixed receivers placed at known locations across the farm. Receivers communicate with tags placed on the ear of each animal to calculate the animal's position. Ear tags send information every three seconds (10 Hz technology for research purposes) to the receivers

which send the information by a wireless connection to an access point that is connected to a central server. Solar panels are utilised to provide power to each of the receivers. While the accuracy of the SMARTBOW system has been tested in an indoor environment (Wolfger *et al.,* 2017), the objective of the current study was to test the accuracy of the system in an outdoor setting when tags remain stationary.

Material and methods

Experimental data

To evaluate the accuracy of position data calculated by the SMARTBOW system, a set of 20 tags were each placed on a 1.5 m pole. Between 10–20 poles with SMARTBOW tags were placed at random locations in each paddock; the exact number of tags placed in each paddock was dependent on paddock size. Location data from 318 positions were collected and each tag was left at the same location for approximately 10 minutes, and consequently had on average 172 ± 41(SD) records. GPS reference points were generated by using a Leica Viva GNNS GS08 Controller in combination with a G607 Smart Antenna (Leica Geosystems, St. Gallen, Switzerland). The accuracy of the Leica Viva GPS device was 5 mm in the horizontal direction and 10 mm in the vertical direction. Before being used as a gold standard for the SMARTBOW tags the Leica Viva device was tested against five points on the farm with known GPS locations. All data were collected on the 12, 13 and 14 June 2018. GPS data from the Leica Viva device were converted to the co-ordinate system used by SMARTBOW (co-ordinate system with the origin placed at the centre of the farm).

Euclidean distance confidence interval

The Euclidean distance (also herein known as the error) between the GPS location and the SMARTBOW location was calculated using the following formula:

$$Euclidean\ distance = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

where (x_1, y_1) and (x_2, y_2) are the co-ordinates of the GPS location and SMARTBOW location, respectively. A histogram of the Euclidean distance was created to visualise the data.

When the Euclidean distance for every point in the dataset was calculated, the dataset was not normally distributed, as expected. The natural log of the Euclidean distance was calculated in order to quantify a one-sided confidence interval (CI). Once the CI of the log of the Euclidean distance was calculated, the exponential function was used to calculate the CI for the Euclidean distance.

Heat maps

To visualise how error changes across the entire farm a heat map was generated.

Results and discussion

Euclidean distance and confidence interval

Results showed that 2.8% of the data had a Euclidean distance greater than 3 m (Figure 6). The mean Euclidean distance was 0.67 m, the one sided 95% confidence interval was 2.75 m and the 99% confidence interval was 4.93 m.

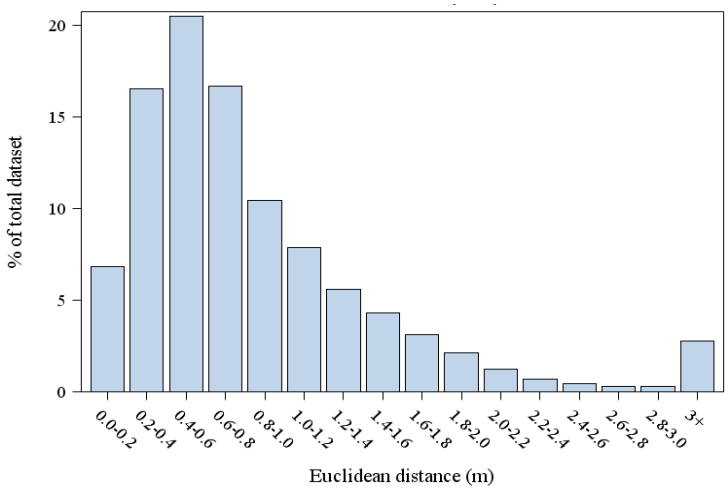

Figure 1. The percentage of SMARTBOW locations at different Euclidean distances away from their respective GPS location

Heat maps

The proportion and location of SMARTBOW tags with Euclidean distances < 1.5 m, between 1.5 m and 3.0 m and > 3 m is shown in Figure 2. While many of the tag locations across the farm contain an error less than 1.5 m, there are certain areas where the error is > 1.5 and < 3 m. Most of the data points where the error is greater than 3 m are located at the extremities of the map. As the data herein was derived from static tags the accuracies are expected to be better than when the tags are moving, therefore, more research is required to test the accuracy of the SMARTBOW system when the tags are in motion throughout the farm.

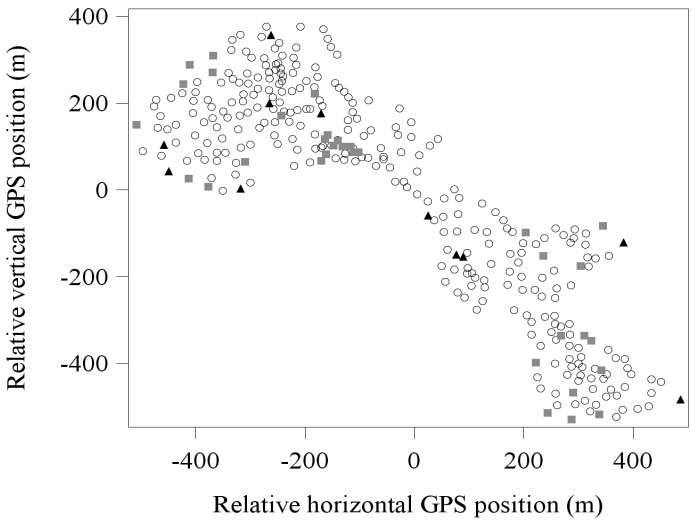

Figure 2. The difference (Euclidean distance) between the SMARTBOW location and GPS location across the farm show differences of < 1.5 m (™), >1.5 m and < 3 m (n) and > 3 m (▲)

Conclusions

The current study suggests that the SMARTBOW system can be used to identify the static locations of tags in a pasture based system with 95% of the data lying within 2.75 m of the true location and 99% of the data lying within 4.97 m of the true location. With such a degree of accuracy the system could be used for farm management and research purposes. System configurations which improve the accuracy of cow localisation will be the next area of research. This will involve the complications of the animal being regularly in motion and the cow's body potentially reducing the number of connected receivers.

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References

Ganskopp, D.C., and D.D. Johnson. (2007). GPS error in studies addressing animal movements and activities. *Rangeland Ecology & Management,* 60(4): 350–358.

Huircán, J.I., C. Muñoz, H. Young, L. Von Dossow, J. Bustos, G. Vivallo, and M. Toneatti. (2010). ZigBee-based wireless sensor network localization for cattle monitoring in grazing fields. *Computers and electronics in Agriculture,* 74(2): 258–264.

Mao, G., B. Fidan, and B.D. Anderson. (2007). Wireless sensor network localization techniques. *Computer Networks*, 51(10): 2529–2553.

Turner, L., M. Udal, B. Larson, and S. Shearer. (2000). Monitoring cattle behavior and pasture use with GPS and GIS. *Canadian Journal of Animal Science,* 80(3): 405–413.

Wolfger, B., B. Jones, K. Orsel, and J. Bewley. (2017). Evaluation of an ear-attached real-time location monitoring system. *Journal of Dairy Science*, 100(3): 2219–2224.

Session 12

Precision Livestock Farming Technology for Pigs

Determining the optimal placement and configuration of an audio-based sensor platform to enable improved detection and characterisation of clinical respiratory episodes in large growing pig airspaces and sites

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Abstract

Audio-based sensor systems have been shown to better detect clinical episodes of respiratory disease. However, microphones used in such systems have distance limits of sound detection. The purpose of this project was to evaluate the optimal placement and configuration of a continuous audio monitoring system in large airspace pig buildings to enable both a high sensitivity for detection and establishing directionality of clinical respiratory episodes. Audio sensor devices were obtained and installed in three large commercial wean-to-finish facilities designed to house 1,200–2,400 pigs per airspace. Five devices were installed in each of two 1,200 head buildings, spaced equidistant from each other along the center alleyway. In the 2,400 head building, 11 devices were installed, with four devices over the middle of the pens on each side of the building spaced equidistant from each other and three in the central alleyway spaced equidistant from each other. Where the device microphone was the center of a circle, the estimated optimal diameter for best detection of cough was determined to be approximately 18-20 meters. For optimal sound coverage in the 1,200 head buildings the optimal number of devices was determined to be four, and for the 2,400 head building the optimal number of devices was determined to be eight. Each device represents an 18-20 meter sound detection 'zone'. The detection and directionality of cough is then a function of the square meters covered by the 'zones' out of the total possible square meters in a barn.

Keywords: cough, respiratory distress, detection radius

Introduction

Producers and veterinarians routinely rely on both observation and data to make clinical assessments of farms and animals, as well as conduct diagnostic investigations to uncover causes and contributing factors of what they judge to be economically and welfare relevant clinical health issues. During the workday and farm walk-through visits, farm personnel and veterinarians use various visual and audio cues to assess the animals and their environment and interpret the cues. Also, recorded daily farm data and production records are reviewed and interpreted to augment observations.

Skills in assessment and interpretation of visual and audio cues, as well as of recorded farm data typically improve with experience. However, these activities can be time-consuming, and are problematic where availability of enough skilled and experienced labor is often a major constraint. Further, the period of animal observation is constrained to typical workday hours, leaving substantial time each day that animals are not observed during at least two-thirds of each weekday as well as by reduced numbers of staff during weekends and holidays. These dynamics can serve to delay detection of clinical health and performance issues, and, in turn, delay interventions – risking welfare, productivity and profitability.

Important audio cues come in the form of sounds like coughing and sneezing of pigs. Sound in the form of cough has been researched for use as a semi-manual clinical assessment and quasi-diagnostic tool (Bahnson *et al.*, 1994; Morris *et al.*, 1995; Nathues *et al.*, 2012) Further, the routine quantification of cough via use of smart devices and an app under commercial conditions has been evaluated for more objective clinical assessment and to better direct diagnostic investigation (Schagemann *et al.*, 2016). While useful, the manual collection of cough data can be problematic under commercial operational conditions. Even when aided by current technologies such as smart phones or tablets and an app, the manual collection of cough data along with management, analysis and interpretation can be time-consuming and require adherence to an execution protocol. Also, while applying a systematic process and related algorithm is more objective than a traditional herd walk-through, a degree of subjectivity still remains where farm production personnel and/or veterinarians are counting coughs.

The need for, value of and various forms of automated and objective assessment and quantification of pig health and welfare have been described, including various categories of technologies useful for these purposes (Matthews *et al.,* 2016). These sensor and device technologies, utilised within in the framework of a coordinated real-time system, can collectively be called 'Precision Livestock Farming'. Precision Livestock Farming (PLF) has been defined as: "…*to manage individual animals by continuous real-time monitoring of health, welfare, production/reproduction, and environmental impact*" (Berckmans, 2017). As a deliverable for the four year EU-PLF project, a "blueprint" for implementation of PLF has been outlined and developed, including descriptions of some PLF technologies (Guarino *et al.*, 2017). Various PLF-oriented technologies have been researched, including sound (VanHirtum & Berckmans, 2002; Guarino *et al.*, 2008). Further, in recent years commercial sound-oriented PLF technologies have begun to be evaluated in commercial settings (Finger *et al.*, 2014; Genzow *et al.,* 2014a; Genzow *et al.,* 2014b; Hemeryck *et al.,* 2015; Polson *et al.,* 2018).

The early detection of clinical respiratory disease in growing pigs can contribute to improved productivity and profitability through enabling earlier, more effective treatment. While clinical disease detection is the direct responsibility of farm personnel detection of clinical disease, onset across multiple farms and systems can be problematic due to variation in their skill, experience and time spent on the farm. Continuous sound monitoring systems can complement and enhance farm personnel and veterinary observation for detection of clinical episodes of respiratory disease. Such systems have been shown to detect the onset of clinical respiratory disease earlier than farm personnel, and hold the potential to do so earlier with greater consistency, reliability, objectivity and precision (Berckmans *et al.,* 2015).

To assess the utility of sound as a 'sample' type in swine for the detection and characterisation of clinical respiratory disease, an audio device, sensors and software platform designed to monitor respiratory distress in pigs were evaluated (SOMO+, SoundTalks NV, Leuven, Belgium). The objective for this evaluation was to determine the optimal placement and configuration of the SOMO+ system in large airspace buildings containing growing pigs to enable both a high sensitivity for detection and establishing directionality of clinical respiratory episodes.

Materials and methods

Three different farm sites / systems were enrolled in the project. Pigs were placed into facilities per normal practice. Cough monitors (SOMO+ Respiratory Distress Monitor, SoundTalks NV, Leuven, Belgium) were obtained and installed in three large commercial wean-to-finish facilities designed to house 1,200–2,400 pigs per airspace (Figure 1).

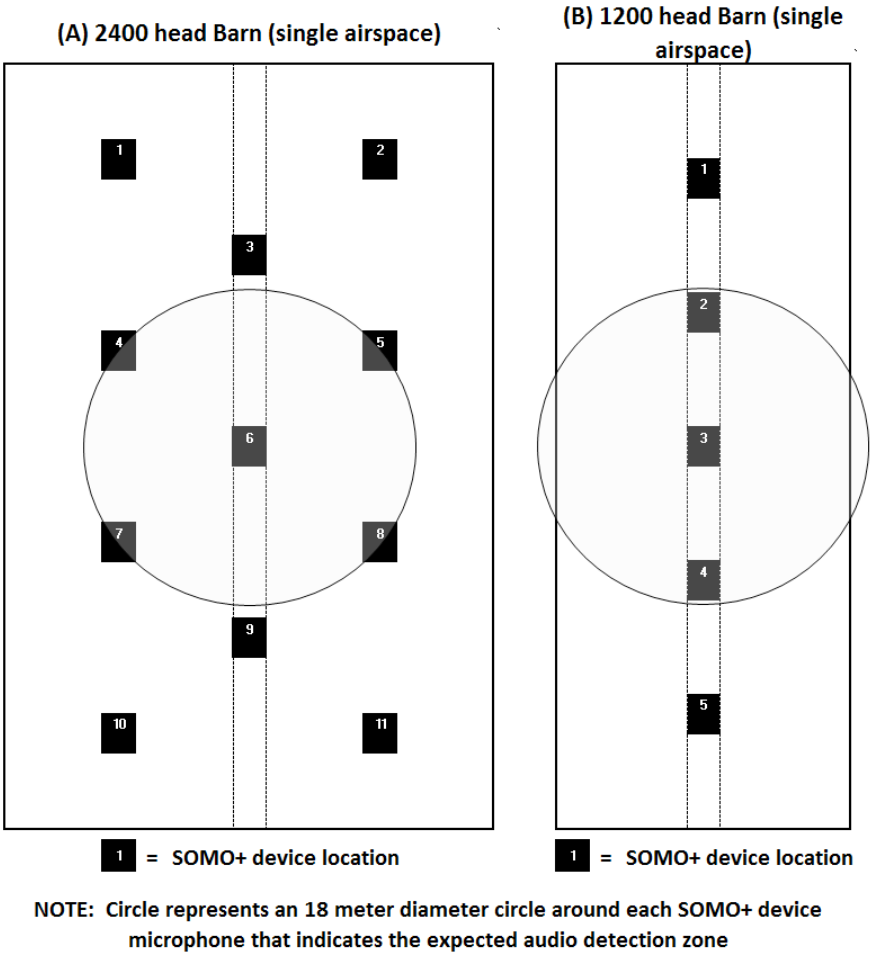


Figure 1. Placement of SOMO+ devices to determine optimal detection zone size, number and configuration to maximise cough detection and directionality determination

Five devices were installed in each of the two 1,200 head buildings, spaced equidistant from each other along the center alleyway. In the 2,400 head building, 11 devices were installed, with four devices over the middle of the pens on each side of the building spaced equidistant from each other and three in the central alleyway spaced equidistant from each other.

Once installed, the SOMO+ devices continuously monitored temperature using two sensors and humidity using one sensor. Also, each device had one connected microphone continuously recording sound. An algorithm was applied to the continuous stream of sound and classified specific sound events as coughs. The sound events classified as coughs were then counted, with the counts uploaded to a cloud database with a web user interface. A mobile app was used to monitor the SOMO+ devices remotely from a smart device (e.g. smart phone or tablet). An algorithm-based respiratory distress index (RDI) was continuously generated from the recorded sound files and cough counts, and was accessible via the web and app interfaces for monitoring and evaluation of various

dynamic visualisation tools, including summary tables and charts.

A correlation analysis was conducted to estimate the optimal sound (cough) detection range for each microphone. The assumptions used for this analysis were:

- Each microphone detects coughs inside a circle of radius R
- Radius R is equal for all microphones
- The circle, defined by R, around each microphone represents a 'hard' boundary, i.e. coughs inside of the circle are reliably detected and coughs outside of the circle are not reliably detected
- Pigs were (relatively) uniformly distributed inside the circle covered by each microphone

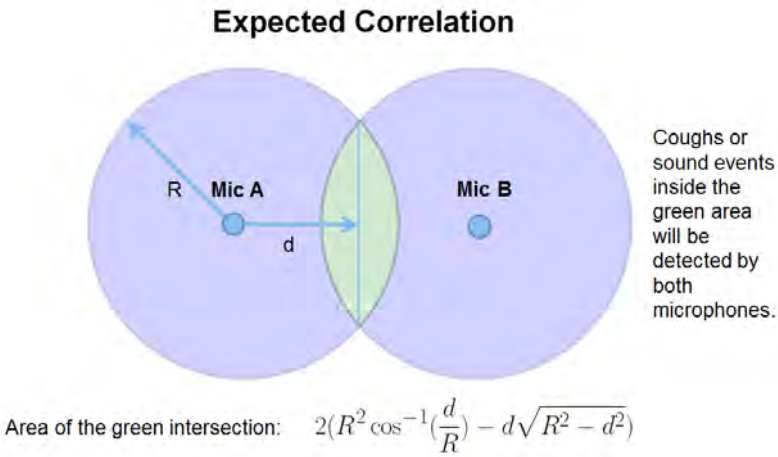


Figure 2. The expected correlation of detected coughs from adjacent microphones with radius R and overlapping audio detection zones

The correlation of detected coughs for each pairing of two different microphones was calculated based on the overlapping (intersecting) area of the circles with radius R around each microphone.

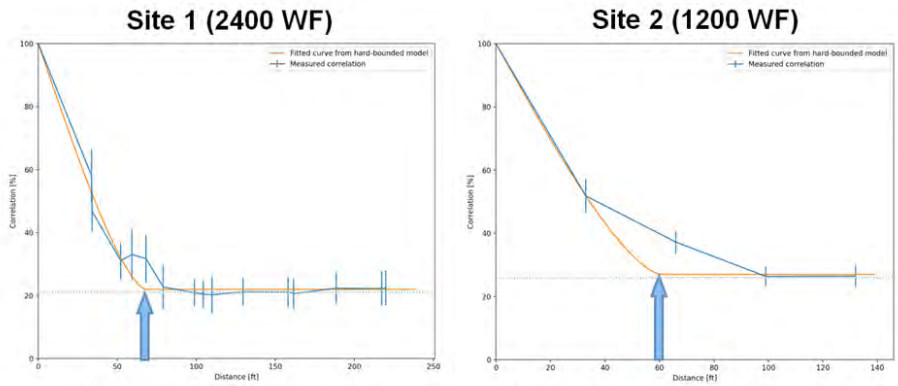
The distance between each pair of microphones was estimated from the barn layout. The cross-correlation was measured for each pair of microphones with overlapping circles, and the computed correlations were plotted as a function of distance between microphones in each pair. Given that the calculated cross-correlations yield finite values (even though cough events detected by two different microphones may not all be correlated), a correlation baseline was determined. Following this, the measured correlation was fit to the correlation predicted by the hard-bounded model. From the plots representing the fit of the measured correlations to the predicted model, estimated of microphone coverage zone (circles) were made for the 2,400 and 1,200 head barns. From these results, the optimal number and placement configuration of microphones (zones) were estimated for the 2,400 and 1,200 head barn types.

Results and discussion

Where the device microphone was the center of a circle, the estimated optimal diameter for best detection of cough was determined to be approximately 18-20 meters. For optimal sound coverage in the 1,200 head buildings, the optimal number of devices was determined

to be three to four, and for the 2,400 head building the optimal number of devices was determined to be six to eight (depending on the length of the building).

Each device represents an 18-20 meter diameter sound detection 'zone'. Within the footprint of an airspace, the detection and directionality of cough is then a function of the square meters covered by the 'zones' out of the total possible square meters in that contiguous airspace. As such, the detection, directionally and movement (ebb and flow) of RDI episodes through the airspace are made possible, enabling better characterisation and understanding of respiratory disease behaviour.



The fitted correlation yields a coverage area of approximately 67ft (20.4m) in diameter and a baseline of 21%.

The fitted correlation yields a coverage area of approximately 60ft (18.3m) in diametre and a baseline of 25%.

Figure 3.

The sensitivity for the detection of and judging the directionality of cough events is then a function of the square meters covered by the 'zones' out of the total possible square meters of animal space in a barn. This dynamic is highly analogous to the impact of sample size and sample selection where sampling pens of animals within airspaces (rooms) of barns and sites – i.e. the hard-bounded 'zone' sampled when using a single rope to collect oral fluids constitutes one pen (sometimes two pens where a single rope is split and hung in both of two pens). Thus, fewer microphones (zones) would be expected to result in decreased cough detection sensitivity and reduce the ability to determine directionality of cough events.

Conclusions

Where the device microphone was the center of a circle, the estimated optimal diameter for best detection of cough was determined to be approximately 18-20 meters. For optimal sound coverage in the 1,200 head buildings, the optimal number of devices was determined to be four and for the 2,400 head building the optimal number of devices was determined to be eight. The detection and directionality of cough is then a function of the square meters covered by the 'zones' out of the total possible square meters in a barn.

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References

Bahnson, P., Marsh, W., Dial, G. (1994). The associations among serology to M. hyopneumoniae, lesions at slaughter, and a clinical index of cough in groups of growing pigs. In: Poomvises P. and Ingkaninun P. (eds) Proceedings. The 13th International Pig Veterinary Society Congress, Tiranasah Press, Bangkok, Thailand, pp. 131.

Berckmans, D. (2017). General introduction to precision livestock farming. *Animal Frontiers* 7(1): 6–11.

Berckmans, D., Hemeryck, M., Berckmans, D. (2015). Animal Sound…Talks! Real-time Sound Analysis for Health Monitoring in Livestock. In: Ni J-Q., Lim Te-T. and Wang C. (eds) Proceedings. The International Symposium on Animal Environment and Welfare, China Agriculture Press, Beijing, China, pp. 215–222.

Finger, G., Hemeryck, M., Duran, C.O., Genzow, M. (2014). Practical application of the Pig Cough Monitor in a German fattening pig herd with PRDC. In: Hernandez J. and Zimmerman J. (eds) Proceedings. The 23rd International Pig Veterinary Society Congress, [IPVS23], Cancun, Mexico, pp. 207.

Genzow, M., Duran, C.O., Strutzberg-Minder, K., Finger, G., Hemeryk, M. (2014). Monitoring of a commercial fattening herd by means of the Pig Cough Monitor and oral fluid diagnostics. In: Hernandez J. and Zimmerman J. (eds) Proceedings. The 23rd International Pig Veterinary Society Congress, [IPVS23], Cancun, Mexico, pp. 205.

Genzow, M., Duran, C.O., Hemeryck, M., Finger, G. (2014). Course of cough in two batches of fattening pigs with different respiratory pathogen exposure. In: Hernandez J. and Zimmerman J. (eds) Proceedings. The 23rd International Pig Veterinary Society Congress, [IPVS23], Cancun, Mexico, pp. 212.

Guarino, M., Jans, P., Costa, A., Aerts J-M., Berckmans, D. (2008). Field testing of algorithm for automatic cough detection in pig houses. *Computers and Electronics in Agriculture*, 62: 22–28.

Guarino, M., Norton, T., Berckmans, D., Vranken, E., Berckmans, D. (2017). A blueprint for developing and applying precision livestock farming tools: A key output of the EU-PLF project. *Animal Frontiers*, 7(1): 13–17.

Hemeryck, M., Berckmans, D., Vranken, E., Tullo, E., Fontana, I., Guarino, M., van Waterschoot, T. (2015). The Pig Cough Monitor in the EU-PLF project: results and multimodal data analysis in two case studies. In: Guarino M. (ed) Proceedings. The 7th European Conference on Precision Livestock Farming, University of Milan, Milan, Italy, pp. 147–155.

Matthews, S., Miller, A., Clapp, J., Plotz, T., Kyriazakis, I. (2016). Early detection of health and welfare compromises through automated detection of behavioural changes in pigs. The *Veterinary Journal,* 217, 43–51.

Morris, C., Gardner, I., Hietala, S., Carpenter, T. (1995). Enzootic Pneumonia: Comparison of Cough and Lung Lesions as Predictors of Weight Gain in Swine. *Canadian Journal of Veterinary Research,* 59(3): 197–204.

Nathues, H., Spergser, J., Rosengarten, R., Kreienbrock, L., Grosse Beilage, E. (2012). Value of the clinical examination in diagnosing enzootic pneumonia in fattening pigs. *The Veterinary Journal,* 193(2): 443–447.

Polson, D., Playter, S., Berckmans, D., Stoffel, A., Quinn, B., Genzow, M., Duran, C.O. (2018). Precision Livestock Farming (PLF) for pig health and production: Sound as a diagnostic sample. In: Culhane M. and Polson D. (eds) Preconference: The 4-dimensional revolution in food animal health and production. The 49th Annual Meeting of the American Association of Swine Veterinarians; San Diego, California USA, [AASV], pp. 21–24.

Schagemann, G., Wertenbroek, N., Langhoff, R., De Jonghe, E., Eppik, L., Figueras, S., Mesu, P. (2016). Cough Control Program for the identification of respiratory pathogens in PRDC farms. In: Martelli P. and Nathues H. (eds) Proceedings. The 24th International Pig Veterinary Society Congress, Royal Dublin Society, Dublin, Ireland, pp. 342.

Van Hirtum, A. and Berckmans, D. (2002). Automated recognition of spontaneous versus voluntary cough. *Medical Engineering and Physics*, 24: 541–545.

Evaluation of a technology platform utilising low power Bluetooth beacons, sensors and a cloud-based platform to concurrently measure near real-time movement of animals, assets and personnel throughout a large pig production network in the United States

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Abstract

The objective of this project was to design, develop and evaluate an integrated measurement system to capture movement records to enable the more objective assessment of movement-related risks of disease introduction and transmission. A large multi-farm system and production network was enrolled in the project. At each participating site zones were outlined, risk levels were assigned, and location beacons were installed. Significant assets were tagged with asset beacons. All system personnel received beacon sensors. Cellular routers with attached gateways were installed. Sensor-captured data was transmitted to a cloud-based platform. This integrated system holds promise as a valuable means for the simultaneous recording of various forms of relevant movements, enabling a much improved understanding of disease introduction and circulation risks in near real-time.

Keywords: movements, risk, beacons, sensors, locations, assets

Introduction

The pig and pork production industry is highly networked and mobile – with various types of movements occurring numerous times per day within farms, between farms, across production systems and throughout production networks. Production systems experience movements of pigs, semen, feed, supplies, assets and personnel – within farm sites, between farm sites, and among non-production sites (e.g. feed mills, truck washes, offices, warehouses). All movements inherently carry with them varying levels of disease introduction and transmission risk by animals, people and/or fomites within and among farm sites, with often serious consequences on animal productivity and business performance.

The objective of this project was to design, develop and evaluate an integrated measurement system to capture movement records of personnel and assets within and among sites to enable the more objective assessment of movement-related risks of disease introduction and transmission.

Materials and methods

Production System Composition

A large multi-farm system and production network in the United States was enrolled in the project. A schematic of the production system live operations sites and pig flow is shown in Figure 1. The system is composed of six large sow farms and sells weaned pigs to grower customers, delivering those weaned pigs to 56 different grower sites. Sow Farm A is a closed-herd multiplier and produces great-grandparent (GGP) and grandparent (GP) replacement animals for itself, as well as parent (P) replacement animals for the other five commercial sow farms. All semen is sourced from an external boar stud.

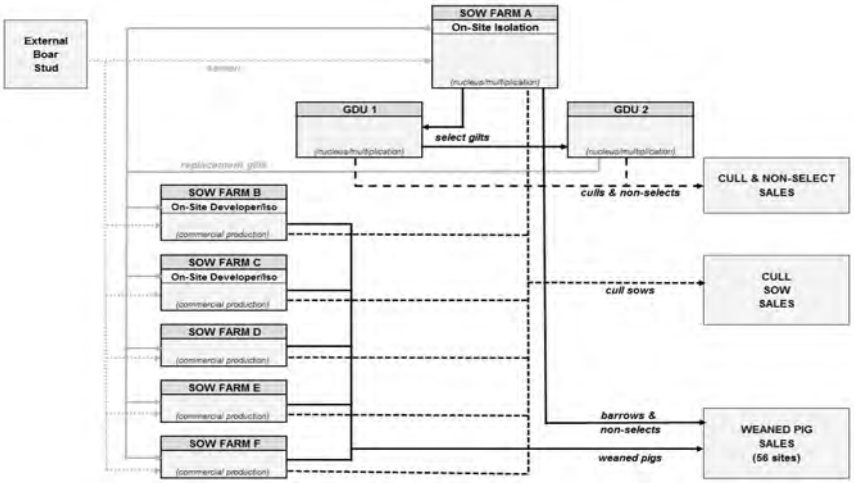

Figure 1. Schematic of production system live operations pig flow

The system has an owned feed mill, and grain is procured from a system-owned crop-production business and corresponding land. Other feed ingredients are purchased from various external suppliers.

The commercial operations of the production system are composed of the following:

- Six sow farm sites (one nucleus/multiplier site, five commercial sites)
- One sow farm scale
- One External boar stud (three semen delivery vehicles, two semen delivery drivers)
- Two gilt development unit (GDU) sites, one GDU scale
- One main office and supply storage
- One feed mill site (one ingredient delivery bay, one feed loading bay)
- One truck wash site (one internal wash bay, one external (over-the-road) wash bay, one dryer bay, one truck shop, one shavings storage)
- One maintenance building, one equipment building
- One rendering dead pickup site
- One rendering plant site (two rendering trucks, two rendering drivers)
- Twelve dumpsters, three garbage trucks, eight dead pickup vehicles + trailers
- Fifty-six grower wean-to-finish (WF) sites
- Three trailer washout sites
- One cull animal marketing site
- One-hundred and four full and part-time employees
- One veterinarian + vehicle
- Fourteen semi trucks, nine internal trailers, seven external (over-the-road) trailers
- Three feed trailers, two grain trailers, four maintenance vehicles, four tractors, 10 pit manure pumps

pTrack System Architecture

The pTrack system is made up of the following system components (Figure 2):

- Bluetooth Low Energy (BLE) Beacons – battery-powered devices that transmit BLE signals
  - » Location beacons – placed in physical locations
  - » Asset beacons – attached to physical assets
- Personnel sensors – battery-powered devices carried by personnel, detect location and asset beacon BLE signals and transmit detection event data to Gateway
- pTrack App – installed on smart phones of personnel, detect location and asset beacon BLE signals and transmit detection event data to Gateway
- Gateways – detect sensors, receive data from sensors, attach via Ethernet cable to cellular routers
- Cellular router – attach to Gateways, transmit data to pTrack Cloud
- pTrack Cloud – receives data from cellular router, contains pTrack web dashboard and control panel (accessible via internet browser with user log-in credentials on PC, laptop, smart phone)

Figure 2. Schematic of pTrack system architecture

pTrack Installation Process

At each animal production site, zones were defined and location beacons were assigned to and placed within each defined zone. For live animal housing space, each zone typically represents an entire barn or an airspace for breeding, gestation and farrowing. For other areas of the farm, defined zones represented specific rooms and work areas (e.g. medication room, tool room, pressure washer room, sow wash area, loadout chute).

Location beacons were installed within each zone. Locations beacons were set to transmit a signal to a radius of 20 meters. The number of location beacons placed in each zone varied, depending on the length × width dimensions of the zone.

Significant assets (e.g. trucks, trailers, feed carts, robots, power washers, semen coolers) were tagged with asset beacons. Asset beacons were set to transmit a signal to a radius of five meters.

Sensor charging stations were installed in the office of each site. All system personnel received beacon sensors to wear while working each day. Cellular routers with attached

gateways were installed in key sites locations. Signage displaying relevant messages and reminders were mounted in visible high-traffic locations within each site.

When a sensor comes within range of a gateway-router tandem, sensor-captured data is automatically transmitted to a cloud-based platform where data can be viewed and analytics done using available visualisation components, dashboards and reports.

A risk level (0 - 10) was assigned to each zone-to-zone movement pair (Figure 3). The assigned risk level was selected based on the estimated risk of movements between two different zones related to their respective zone characteristics.

Origin \ Destination	MWFBGF Isolation	MWFBGF Gestation 1	MWFBGF Gestation 2	MWFBGF Gestation 3	MWFBGF Gestation 4	MWFBGF Farrowing 1
MWFBGF Isolation		4	4	4	4	6
MWFBGF Gestation 1	2		0	0	0	2
MWFBGF Gestation 2	2	0		0	0	2
MWFBGF Gestation 3	2	0	0		0	2
MWFBGF Gestation 4	2	0	0	0		2
MWFBGF Farrowing 1	2	0	0	0	0	
MWFBGF Farrowing 2	2	0	0	0	0	0
MWFBGF Office	2	0	0	0	0	0
MWFBGF Dead Box	10	10	10	10	10	10
MWFBGF Gate	2	2	2	2	2	2
MWFBGF Iso East Chute	0	4	4	4	4	6
MWFBGF Iso West Chute	0	4	4	4	4	6

Figure 3. Input matrix for assigning origin-to-destination zone personnel and asset movement risk levels (Note: axis zone name labels are hidden to protect anonymity)

Examples of lower and higher risk movements are as follows:

- A movement from a gestation zone to a loadout chute zone was assigned a relatively lower risk
- A movement from an isolation room to a gestation barn was assigned a relatively higher risk

When personnel carrying sensors come within range of a location beacon in a defined zone and remain within that zone for a specified period of time, the sensor detects the location beacon signals assigned to that zone and records the ID, date and time as a detection event for that zone. The time required for a sensor to record a detection event is a variable specified by the administrator, and depends on where the zone and corresponding location beacons are located. For example, zones with location beacons placed in driveway entries were set with a very short time period to record drive-by movement events; whereas zones with location beacons placed in farrowing or gestation barns were set with a relatively longer time period.

When personnel carrying sensors come within range of an asset beacon, the sensor detects the asset beacon signal and records the ID, date and time as a detection event. When personnel carrying sensors and beacon tagged assets enter within range of location beacons in a defined zone, the sensor records the asset-within-zone event.

Results and discussion

System installation began in mid-2018 and continued through 2018. Further site installations will continue through mid-2019 for more distant sites distributed throughout the production system network. As this is intended to be a long-term multi-year pilot project, personnel and asset movements will continue to be recorded and evaluated on an ongoing basis. Also, updates and adjustments to hardware, software, risk levels and protocols will continue to be made as necessary based on user feedback and project observation.

Figure 4 shows an example of two forms of personnel and asset movement visualization – movement arrows and a heat-map. Movement arrows indicate source (Sow Farm A office zone) to destination (farrowing and gestation zones) movements with the number of movements in the period displayed at the destination zone (tip of the arrow). The colour of arrow corresponds to the assigned risk level for the respective zone-to-zone movements. The colour of a destination zone on the heat map format corresponds to the number of movements in period being displayed, with "hotter" colours (e.g. red) indicating more movements than "cooler" colors (e.g. green).

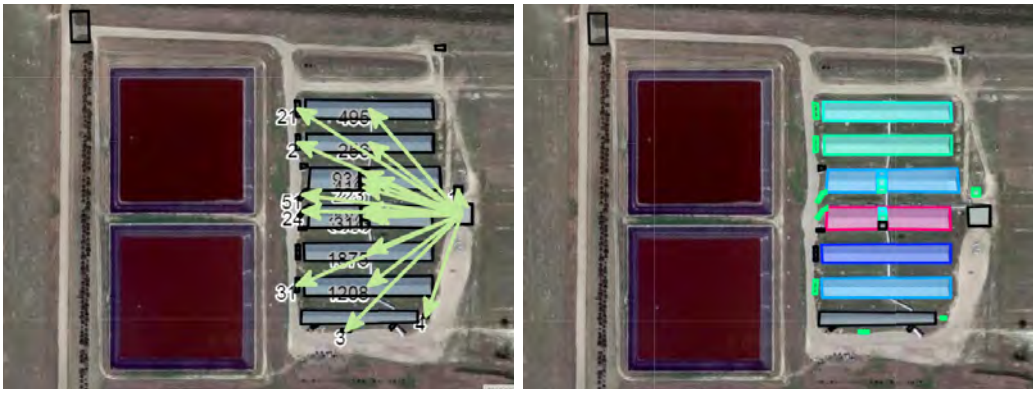

Figure 4. Examples of personnel and asset movements over a 31 day period in Sow Farm A displayed on satellite map. Left image: arrows from source to destination with number of movements (colour of arrow corresponds to risk level); Right image: heat map of destination movement intensity (colour of zone corresponds to number of movements in period being displayed)

Figure 5 is an example of a time-series chart of daily zone-to-zone personnel and asset movements. Figure 6 is an example of day-of-week and hour-of-day graphs. Within each day movement risk levels are displayed as a stacked bar for both Figures 5 and 6. With this being a preliminary evaluation of the first implementation of its kind with this technology platform, expected levels, ranges and distributions of movement risk values cannot yet be determined.

Figure 7 is an example of an origin zone-to-destination zone movement scatterplot. The colour of the bubbles corresponds to the assigned zone-to-zone risk levels. The size of the bubbles corresponds to the number of movements for each respective zone-to-zone pairing.

These visuals can assist users with identifying dates, times and locations of unexpected high-risk movements of assets and/or personnel. This knowledge can help production management staff to work with personnel to mitigate and manage disease transmission and circulation risks within and among sites for entire production networks.

As this production system network pilot project continues, hardware performance, software usefulness and personnel compliance will be assessed. Where improvements are needed, adjustments and modifications will be made.

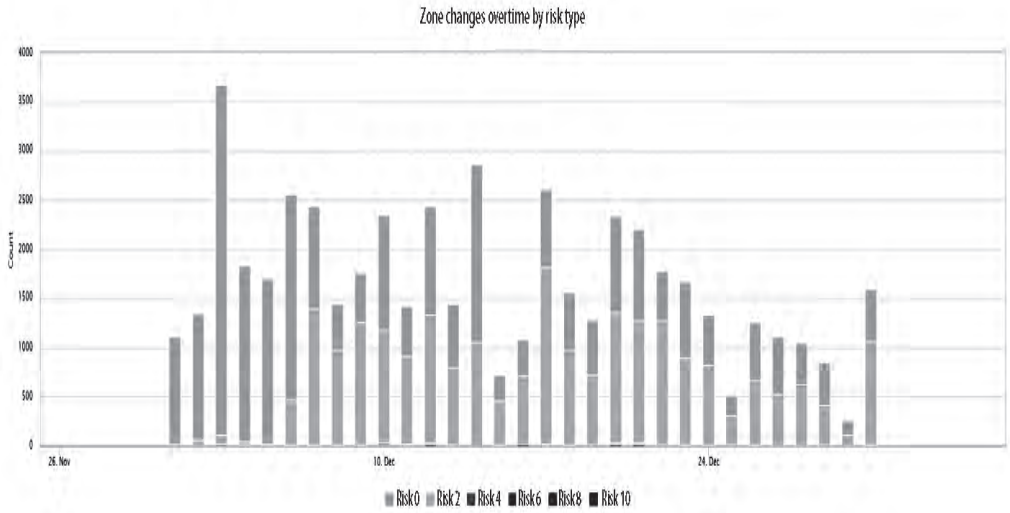

Figure 5. Example of a time-series chart stacked by risk level of daily personnel and asset movements over a 31 day period in Sow Farm A

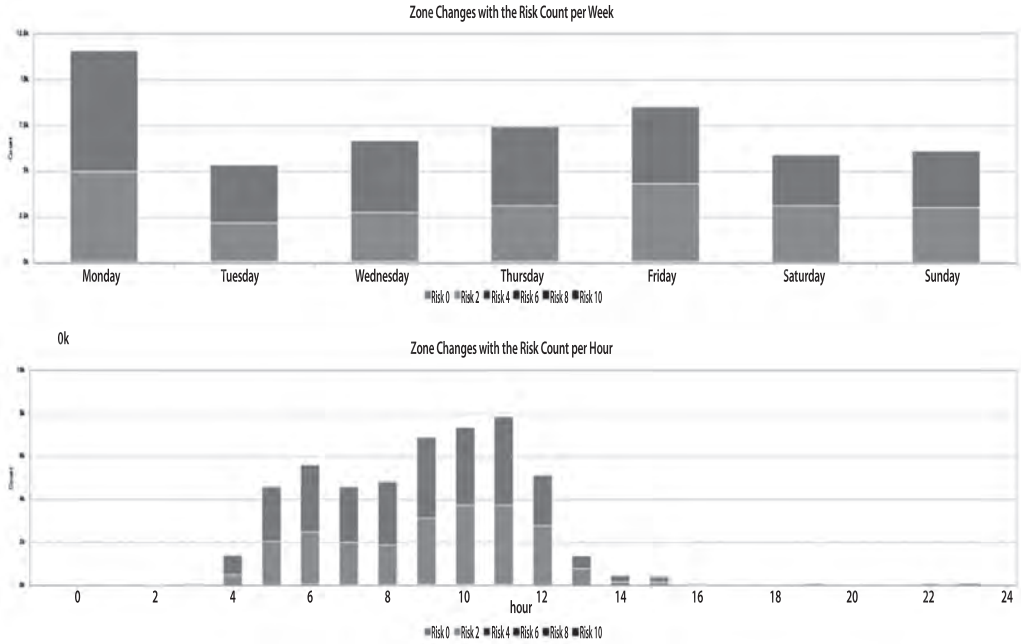

Figure 6. Example of a day-of-week and hour-of-day movements over a 31 day period in Sow Farm A

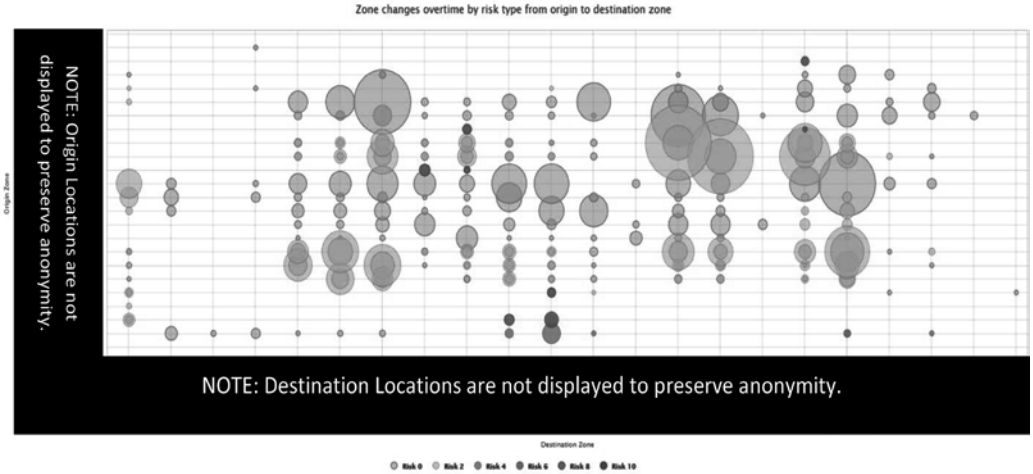

Figure 7. Scatter plot of Origin location (Y-axis) to Destination location (X-axis) movements over a 31 day period in Sow Farm A (Note: X and Y axis zone name labels are hidden to protect anonymity)

Conclusions

This is a preliminary evaluation of the first system-scale implementation of the pTrack technology in pig production. The pTrack integrated movement system holds promise as a valuable means for the simultaneous recording of various forms of relevant personnel and asset movements, enabling a much improved understanding of disease introduction and circulation risks within and among sites across production networks in near real-time. Further enhancements to the existing platform technology, as well as integration of additional technologies into the platform are planned. As this and any additional implementations progress, opportunities are expected to arise for assessing the platforms investigative contribution towards understanding the source(s) of disease agent introduction and continued circulation within and between farms.

Acknowledgements

A big thank you goes out to the pTrack crew who worked on the installation: Jeff, Jens, Kellie, Steve, Erin, Greg, Tyler, Jordi, Gabriel, Cesar, Fausto. A special thank you is due to Tyler for handling a major share of the ongoing work for the project. Finally, thank you to the production system management for allowing us to conduct this project in their system, and to their many team members who are cooperating in the project.

Evaluation of low-cost depth cameras for precision livestock farming applications

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Abstract

Low-cost depth-cameras have been used in many PLF applications. The cameras use one or a combination of three technologies: structured light, time of flight (TOF), and stereoscopy. The objectives were to evaluate different technologies for depth sensing including measuring accuracy and repeatability of distance data and measurements at different positions within the image, and cameras usefulness in indoor and outdoor settings. Then, each camera was tested in a swine facility. Five different cameras were used: (1) Microsoft Kinect v.1, (2) Microsoft Kinect v.2, (3) Intel® RealSense™ Depth Camera D435, (4) ZED Stereo Camera (StereoLabs), and (5) CamBoard Pico Flexx (PMD Technologies). Results indicate that there were significant differences for all cameras ($P < 0.05$), except for TOF cameras (Kinect v.2 and Flexx). All cameras showed an increase in the standard deviation as the distance between camera and object increased; however, the Intel camera had a larger increase. TOF cameras had the smallest error between different sizes of objects. All cameras showed some distortion at the edges of the images. TOF cameras had non-readable zones on the corners of the images. All cameras except ZED captured a recognisable image of a pig within the swine facility. In conclusion, understanding the errors associated with each type of technology is needed. It appears from these results that the time-of-flight technology is the best to be used for indoor PLF applications.

Keywords: Image technology, depth sensors, time of flight, stereoscopic, structured light

Introduction

Precision livestock farming application originally used standard digital image processing and analysing, but problems with this approach, such as lighting, colour distinction, and excess of equipment, led to the use of depth cameras. Low-cost cameras have been used in a number of precision livestock farming publications (Condotta *et al.*, 2018; Guo *et al.,* 2017; Kongsro, 2014; Lao *et al.,* 2016; Lee *et al.,* 2016; Stavrakakis *et al.,* 2015; Wang *et al.,* 2018).

There are several technologies used for depth acquisition: stereo vision, structured light, time of flight and combination of these technologies. Stereo vision uses two digital parallel viewcameras and calculates depth by estimating disparities between matching keypoints in the left and right images. Structured light technology uses a projected light pattern and a camera system to detect distances. Time of flight depth sensors emit a very short infrared light pulse and each pixel of the camera sensor measures the return time. Each of these technologies has advantages and disadvantages associated with them.

The most common cameras cited in publications are Kinect v.1 (structured light technology) and Kinect v.2 (time of flight technology). However, Kinect v.1 was discontinued in the spring of 2015 and Kinect for V2 was discontinued in fall of 2017. With these discontinuations, researchers and product developers were left wondering which cameras to use. The objective of this paper was to test different types of depth cameras to determine the best technology to use in housed livestock PLF applications.

Material and methods

Five different types of cameras were used: (1) Microsoft Kinect v.1, (2) Microsoft Kinect v.2, (3) Intel® RealSense™ Depth Camera D435, (4) ZED Stereo Camera (StereoLabs), and (5) CamBoard Pico Flexx (PMD Technologies) (Figure 1). These cameras represent different technologies currently being used in low-cost depth sensors: Structured light (SL), Time of Flight (ToF), Stereo Vision, and SV combined with SL. Two ToF cameras are being tested because Microsoft Kinect v.2 has been discontinued and, at the same time, is one of the most used depth cameras in PLF research.

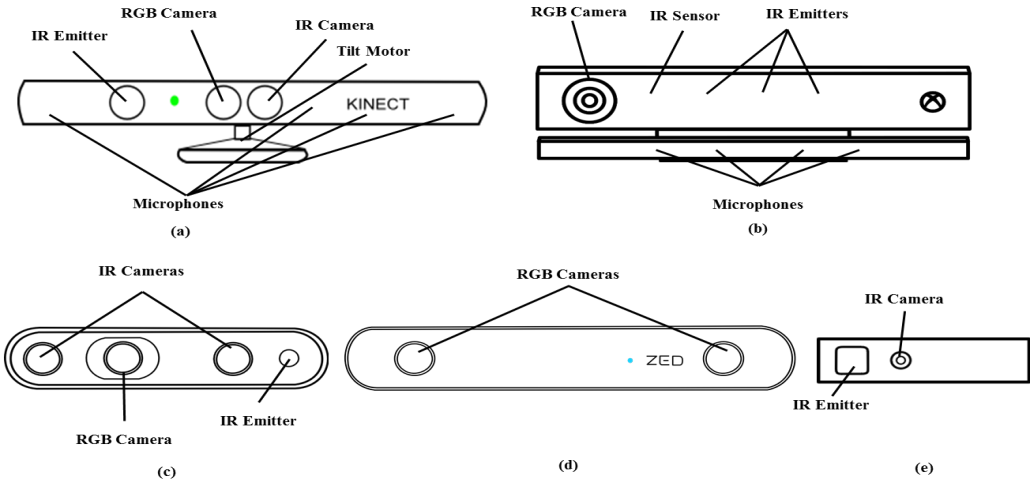

Figure 1. Components of commercial depth cameras being used in this study (out of scale). (a) Microsoft Kinect v.1, (b) Microsoft Kinect v.2, (c) Intel® RealSense™ Depth Camera D435, (d) ZED Stereo camera (StereoLabs) and (e) CamBoard Pico Flexx (PMD Technologies)

Two types of programs were developed: (1) image acquisition programs and (2) image processing programs. Image acquisition programs were written for each of the cameras; some required a specific programming environment. The acquisition program was deployed on a Windows-based PC or a specific microcomputer board. For Flexx and the Kinect cameras v.1 and v.2, a numerical computing software (MATLAB, R2018a) on a Windows PC was used. For Intel camera, a C++ program was developed on a UP Core microcomputer board with an Ubuntu kernel using Intel® RealSense™ SDK, and, for ZED camera, a C++ program was developed on an NVIDIA Jetson TX2 microcomputer board, also with an Ubuntu kernel, using ZED SDK. All the image processing programs were developed on a Windows PC using MATLAB, R2018a.

Several tests were conducted using all five cameras including distance accuracy and repeatability, dimension accuracy and repeatability, indoor use, and demonstration using grow-finish pigs in an indoor facility with no outside light.

Distance accuracy and repeatability was tested using three depth cameras of each type at a total of five different distances. Repeatability between cameras was tested using three depth cameras of each type. Five depth images and five RGB images (except for Pico Flexx) of the wall were collected with each camera at five distances (from 1.0–3.0 meters, every 0.5 m). Depth images were processed with an algorithm developed to extract a fixed area of 11 × 11 pixels at the center of the wall. These points were recorded and, then, the average and the standard deviation were calculated. Comparison between cameras was made by using the Efroymson's algorithm ("stepwise" regression) (Efroymson, 1960).

Dimension accuracy and repeatability was also tested using three cameras of each type. Three sizes of poster board squares (10, 20, 30 cm^2) were recorded at five distances (1.0–3.0 m; every 0.5 m) and four different positions on the image (center, right center edge, bottom center edge, and right bottom corner; Figure 2). A total of five depth and RGB images (except Flexx) from each of the three replicates of the five types of cameras.

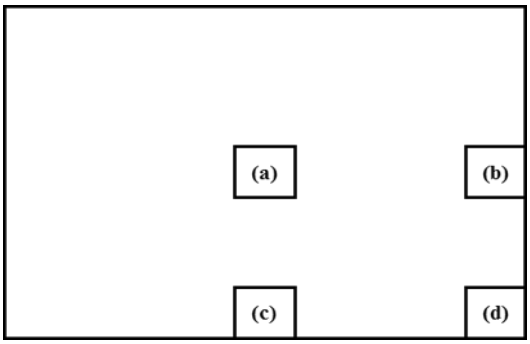

Figure 2. Positions used for images acquisition: (a) center of image, (b) edge on the horizontal axis of the image, (c) edge on the vertical axis of the image and (d) corner of the image

The data were analysed to obtain three different parameters: length, area, and volume of the squares. The length of the square (in pixels) was obtained both for the RGB image (except for Flexx) and the depth image. For the RGB images, a manual measure process was performed, using the Image Viewer application from MATLAB R2018a.

The length ratio, in pixel cm^{-1}, was calculated dividing the length in pixels, obtained for both RGB (when available) and depth images, by the actual length of the foam board square (either 10, 20 or 30 cm). Furthermore, the area ratio, in px cm^{-2}, was also calculated by dividing the area obtained on the depth image (in pixels) by the actual area of the squares (either 100, 400 or 900 cm^2).

These ratios were analysed using the General Linear Procedure (proc GLM) of SAS software, testing the effects of the use of different positions (center, edge on the horizontal axis of the image, edge on the vertical axis of the image and corner) and different sizes (10 × 10 cm, 20 × 20 cm and 30 × 30 cm) of foam board squares used. Then, regression models were generated for length ratio (px cm^{-1}) versus distance from the camera to object, and for the area ratio (px cm^{-2}) versus distance.

Unit transformation equations were developed to eliminate the need for the presence of an object with a predetermined size to acquire dimensions of an image, as has been used by several authors (Philips & Dawson, 1936; Zaragoza, 2009). To obtain these equations, regression models were developed from known object sizes and the known distances.

The livestock experiment was conducted in a grow-finish building at the USDA-ARS Meat Animal Research Center (USMARC) in Clay Center, Nebraska (-98.13° W, 42.52° N). All animal procedures were approved by the USMARC IACUC and followed recognised guidelines for animal use and care (FASS, 2010). Top view images were captured on a sample group grow-finish pigs for demonstration purposes.

Results and discussion

Distance accuracy and repeatability tests are summarised in Table 1. The average values of distance obtained for the region of the wall in the picture, as well as their respective standard deviations, are shown in Table 1. The result of the Efroymson's algorithm showed

that the behaviour of different cameras of the same type is the same for cameras that use the ToF principle, Flexx (P = 0.18710) and Microsoft Kinect v.2 (P = 0.70697), but different for the other types of cameras, Intel (P = 0.02538), Microsoft Kinect v.1 (P = 0.00002) and ZED Stereo Camera (P = 0.00007). From Table 1 it can be noted that there is an increase in the standard deviation with increasing distance from sensor to wall, corroborating with the data obtained by Khoshelham & Elberink (2012).

Table 1. Average distances (m) and standard deviation (m) obtained by five depth cameras, for the five analysed distances with their respective standard deviations. One hundred and twenty-one points were used for each image to gather each value, and three cameras of each type were used

	Distances from sensor to wall (m)					
Camera	**1.00**	**1.50**	**2.00**	**2.50**	**3.00**	**P-value**
CamBoard Pico Flexx	0.99 ± 0.001	1.48 ± 0.002	1.99 ± 0.003	2.50 ± 0.004	3.00 ± 0.006	0.18710
Intel® RealSense™ D435	0.99 ± 0.002	1.47 ± 0.012	1.97 ± 0.022	2.46 ± 0.035	2.97 ± 0.036	0.02538
Microsoft Kinect v.1	0.99 ± 0.002	1.49 ± 0.003	1.99 ± 0.006	2.49 ± 0.008	3.00 ± 0.013	0.00002
Microsoft Kinect v.2	1.00 ± 0.001	1.50 ± 0.001	2.01 ± 0.001	2.51 ± 0.002	3.01 ± 0.003	0.70697
ZED Stereo Camera	0.99 ± 0.001	1.48 ± 0.001	1.99 ± 0.002	2.48 ± 0.004	2.99 ± 0.003	0.00007

Unit transformation equations were developed from regression models between the area (px cm^{-2}) and length (px cm^{-1}) ratios and the distance (m) from the camera to the foam board square. Table 2 contains the coefficients of these equations for depth images.

To calculate the volume of objects from the depth map, there is a need to convert px to cm. As the distance data provided by the sensors are in cm and the area of the object is given in the number of pixels, the volume is retrieved in an unwanted unit (px cm). Another correction is needed to ensure the volume is correct regardless of distance from the camera.

Table 2. Coefficients a and b for unit transformation equations from px to cm (length) and from px to cm^2 (area) on depth images provided by five depth cameras

	Length coefficients		R^2	Area coefficients		R^2
Camera	**a[1]**	**b**		**a[2]**	**b**	
CamBoard Pico Flexx	0.475	1.014	0.993	0.230	2.023	0.998
Intel® RealSense™ D435	0.147	0.896	0.912	0.023	2.004	0.853
Microsoft Kinect v.1	0.165	0.973	0.980	0.030	1.940	0.988
Microsoft Kinect v.2	0.272	1.000	0.996	0.075	2.058	0.977
ZED Stereo Camera	0.063	0.986	0.972	0.005	1.986	0.973

[1] $length_{cm} = length_{px} \times a \times Distance\ from\ the\ camera^b$;
[2] $area_{cm}^2 = area_{px} \times a \times Distance\ from\ the\ camera^b$

Three sizes of foam board squares were used to test the effects of object size on the length (px cm^{-1}) and area (px cm^{-2}) ratios. The smallest object (10 × 10 cm) had a significant different area ratio than the other sizes for all cameras except Flexx. This is due to edge deformation effect being more pronounced on the small objects, as indicated by Gottfried *et al.* (2011). Kinect v.1 showed differences between all sizes of squares used for both length ratio and area ratio, and ZED showed differences between all sizes of square used when measuring length ratio. This indicates these cameras had a larger edge effect, thus impacting the size of both the 10 ×10 cm and the 20 × 20 cm boards (Table 3).

Impacts on length and area ratios of objects' position within the image varied for each type of camera used. For the ToF cameras (Flexx and Kinect v.2), all positions have different length ratios. The area ratio for Flexx camera is the same between positions 1 and 3 (center and edge on vertical axis) and between positions 2 and 4 (edge on horizontal axis and corner). The area ratio for Kinect v.2 is the same between positions 1 and 2, and between 1 and 4; position 3 (edge on vertical axis) differs from the others.

For acquiring length ratio with Intel, position 1 (center) differs from the others, position 3 (edge on vertical axis) has the same effect as positions 2 (edge on horizontal axis) and 4 (corner). The effect of positions on the area ratio for this camera was the same presented by Kinect v.1 for both length and area ratios, positions 1 and 2 have the same behaviour and positions 3 and 4 have the same behaviour (Table 4).

Table 3. Averages and standard errors obtained for length ratio (px cm^{-1}) and area ratio (px cm^{-2}), for the three sizes of square used (10 × 10 cm, 20 × 20 cm and 30 × 30 cm) and five different depth cameras

Camera	Square Size (cm)	Length Ratio (px cm^{-1})	Area Ratio (px cm^{-2})
CamBoard Pico Flexx	10 x 10	1.20 ± 0.01^{a}	1.54 ± 0.02
	20 x 20	1.17 ± 0.01^{b}	1.54 ± 0.02
	30 x 30	1.17 ± 0.01^{b}	1.55 ± 0.02
Intel® RealSense™ D435	10 x 10	4.84 ± 0.06^{a}	21.58 ± 0.39^{a}
	20 x 20	4.24 ± 0.06^{b}	17.65 ± 0.39^{b}
	30 x 30	4.11 ± 0.06^{b}	16.85 ± 0.39^{b}
Microsoft Kinect v.1*	10 x 10	3.92 ± 0.17^{a}	15.08 ± 0.14^{a}
	20 x 20	3.61 ± 0.17^{b}	13.84 ± 0.14^{b}
	30 x 30	3.50 ± 0.17^{c}	13.16 ± 0.14^{c}
Microsoft Kinect v.2*	10 x 10	2.33 ± 0.15^{a}	5.56 ± 0.05^{a}
	20 x 20	2.19 ± 0.15^{b}	5.25 ± 0.05^{b}
	30 x 30	2.15 ± 0.15^{b}	5.11 ± 0.05^{b}
ZED Stereo Camera	10 x 10	9.87 ± 0.07^{a}	90.50 ± 1.77^{a}
	20 x 20	9.34 ± 0.07^{b}	85.43 ± 1.77^{b}
	30 x 30	9.04 ± 0.07^{c}	83.18 ± 1.77^{b}

[a, b, c] Rows for each column, with different superscripts are significantly different ($p<0.05$)
* Microsoft Kinect v.1 showed significant interaction between position and size of the foam board square for length ratio. Microsoft Kinect v.2 showed significant interaction between position and size of the foam board square for both area ratio and length ratio. ZED Stereo Camera showed significant interaction between camera and size of the foam board square for length ratio

Dutta (2012), showed that the standard deviation of the distance data increases on the corners of the image. Thus, the ideal for data comparison of length and area acquired with

depth sensors is positioning it at a fixed region of the image, preferably in the centre. If offsets need to be made, it would be ideal to offset the objects on the horizontal direction of the image for Intel and Kinect v.1, and on the vertical direction of the image for Flexx and Kinect v.2; in which the differences are smaller, reducing distortion of values and enabling data comparison. ZED did not present any effect of positions on the length and area ratios acquisition and, thus, the objects can be positioned in any place on the image.

Kinect v.1 camera showed significant interaction between position and size of the foam board square for length ratio. Kinect v.2 showed significant interaction between position and size of the foam board square for both area ratio and length ratio. ZED showed significant interaction between camera and size of the foam board square for length ratio.

Table 4. Averages and standard errors obtained for length ratio (px cm^{-1}) and area ratio (px cm^{-2}), for the four positions on image (1 - center, 2 - edge on the horizontal axis, 3 - edge on the vertical axis, 4 - corner) and five depth cameras

Camera	Position	Length Ratio (px cm^{-1})	Area Ratio (px cm^{-2})
CamBoard Pico Flexx	1	1.21 ± 0.01^{a}	1.69 ± 0.03^{a}
	2	1.08 ± 0.01^{b}	1.41 ± 0.03^{b}
	3	1.28 ± 0.01^{c}	1.68 ± 0.03^{a}
	4	1.14 ± 0.01^{d}	1.40 ± 0.03^{b}
Intel® RealSense™ D435	1	4.16 ± 0.07^{a}	16.98 ± 0.45^{a}
	2	4.38 ± 0.07^{b}	17.85 ± 0.45^{a}
	3	4.46 ± 0.07^{bc}	19.60 ± 0.45^{b}
	4	4.58 ± 0.07^{c}	20.34 ± 0.45^{b}
Microsoft Kinect v.1*	1	3.56 ± 0.02^{a}	13.44 ± 0.17^{a}
	2	3.61 ± 0.02^{a}	13.82 ± 0.17^{a}
	3	3.78 ± 0.02^{b}	14.48 ± 0.17^{b}
	4	3.76 ± 0.02^{b}	14.37 ± 0.17^{b}
Microsoft Kinect v.2*	1	2.14 ± 0.02^{a}	5.13 ± 0.06^{ab}
	2	2.09 ± 0.02^{b}	5.03 ± 0.06^{a}
	3	2.42 ± 0.02^{c}	5.86 ± 0.06^{c}
	4	2.27 ± 0.02^{d}	5.21 ± 0.06^{b}
ZED Stereo Camera	1	9.35 ± 3.89	86.70 ± 75.07
	2	9.28 ± 3.77	82.41 ± 67.40
	3	9.46 ± 3.64	86.81 ± 67.09
	4	9.59 ± 3.93	89.56 ± 73.07

[a, b, c, d] Rows for each column of each camera section, with different superscripts are significantly different ($p<0.05$); *Microsoft Kinect v.1 showed significant interaction between position and size of the foam board square for length ratio. Microsoft Kinect v.2 showed significant interaction between position and size of the foam board square for both area ratio and length ratio

Figure 3 shows examples of area and length of a 30 × 30 cm foam board square acquired with the five different cameras used in this study and with units corrected. Kinect v.1 was

most consistently accurate across the different distances in lengths and areas. The TOF cameras overestimated lengths but the two TOF cameras were very similar. TOF cameras also overestimated areas, but the two cameras did not consistently match. Both Intel and ZED underestimated length and area and were not consistent on the underestimation when the distance from the camera changed.

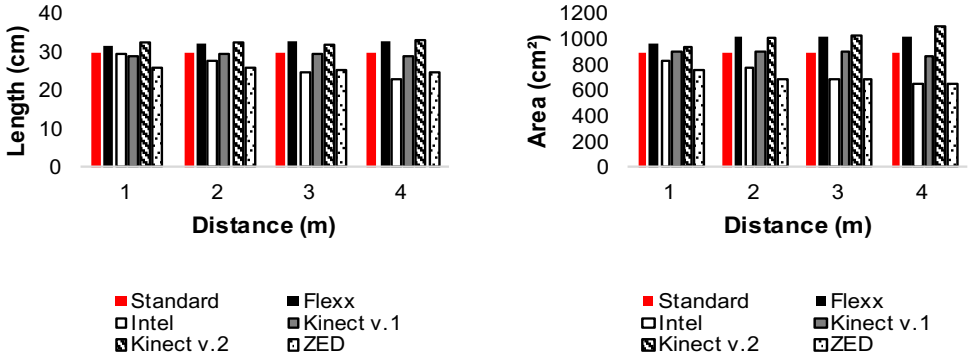

Figure 3. Predicted area and length of foam squares recorded with five depth cameras (CamBoard Pico Flexx, Intel® RealSense™ D435, Microsoft Kinect v.1, Microsoft Kinect v.2, and ZED Stereo Camera)

Top view images were taken on a group of pigs as they were being weighed. Figure 4 shows the sample of the images captured. As the images are evaluated, all the pigs are easily visible in all the images except the image captured from ZED. The main body is easily seen, but the head and the tail are difficult to discern. The image taken with Kinect v.1 has rough edges on the pig. The slightly rough edges are also observed on the image taken with the Real Sense camera. Both TOF cameras had a clear image, of the two, Kinect v.2 have the smoothest outline of the pigs. Kinect v.2 with the higher resolution has the nicest image.

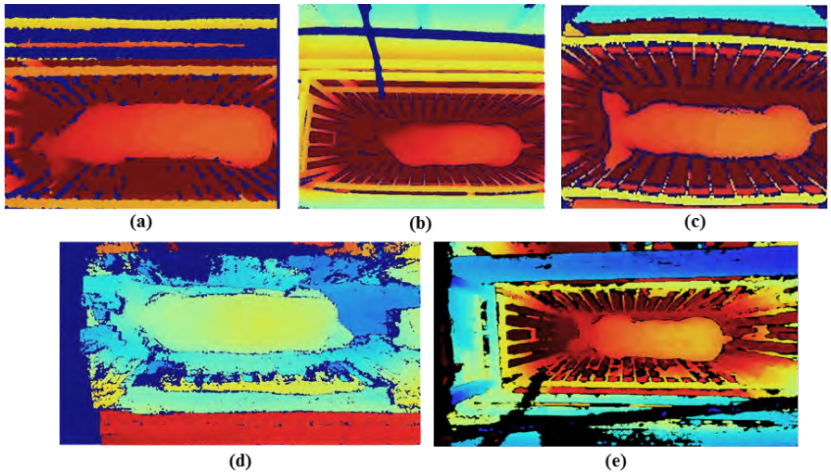

Figure 4. Depth images acquired from the pigs for all five cameras used: (a) Microsoft Kinect v.1, (b) Microsoft Kinect v.2, (c) CamBoard Pico Flexx (PMD Technologies), (d) ZED Stereo camera (StereoLabs) and (e) Intel® RealSense™ Depth Camera D435

Conclusions

Low-cost depth-cameras use one or a combination of three technologies: structured light, time of flight (TOF), and stereoscopy. Five different cameras were tested for their suitability to be used in PLF applications. Significant camera to camera differences were found for all the cameras ($P < 0.05$), except for TOF cameras (Kinect v.2 and Flexx). Increases in standard deviation in measurements were found with all cameras as the distance between camera and object increased; however, Intel camera had a much larger increase. TOF cameras had the smallest error between different sizes of objects. All cameras showed some distortion at the edges of the images; however, the TOF cameras had non-readable zones on the corners of the images. All cameras except ZED captured a recognisable image of a pig within the swine facility. In conclusion, understanding the errors associated with each type of technology is needed. It appears from these results that the TOF technology is the best suited for indoor PLF applications.

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References

Condotta, I.C.F.S., Brown-Brandl, T.M., Silva-Miranda, K.O., & Stinn, J.P. (2018). Evaluation of a depth sensor for mass estimation of growing and finishing pigs. *Biosystems Engineering*, 173:11–18.

Dutta, T. (2012). Evaluation of the Kinect sensor for 3-D kinematic measurement in the workplace. *Applied Ergonomics*, 43(4): 645–649.

Efroymson, M.A. (1960). Multiple regression analysis. *Mathematical Methods for Digital Computers*, edited by: Ralston, A. and Wilf, HS.

Gottfried, J, J. Fehr and C.S. Garbe, Computing Range Flow from Multi-modal Kinect Data. Advances in Visual Computing, 2011, 758–76.

Guo, H., Ma, X., Ma, Q., Wang, K., Su, W., & Zhu, D.H. (2017). LSSA_CAU: An interactive 3d point clouds analysis software for body measurement of livestock with similar forms of cows or pigs. *Computers and Electronics in Agriculture*, 138: 60–68.

Khoshelham, K., & Elberink, S.O. (2012). Accuracy and resolution of Kinect depth data for indoor mapping applications. *Sensors*, 12(2): 1437–1454.

Kongsro, J. (2014). Estimation of pig weight using a Microsoft Kinect prototype imaging system. *Computers and Electronics in Agriculture*, 109: 32–35.

Lao, F., Brown-Brandl, T., Stinn, J.P., Liu, K., Teng, G., & Xin, H. (2016). Automatic recognition of lactating sow behaviors through depth image processing. *Computers and Electronics in Agriculture*, 125: 56–62.

Lee, J., Jin, L., Park, D., & Chung, Y. (2016). Automatic recognition of aggressive behavior in pigs using a Kinect depth sensor. *Sensors (Switzerland)*, 16(5).

Phillips, R.W., & Dawson, W.M. (1936). A study of methods for obtaining measurements of swine. *Proceedings of the American Society of Animal Nutrition*, 1936(1): 93–99.

Stavrakakis, S., Li, W., Guy, J.H., Morgan, G., Ushaw, G., Johnson, G.R., & Edwards, S.A. (2015). Validity of the Microsoft Kinect sensor for assessment of normal walking patterns in pigs. *Computers and Electronics in Agriculture*, 117: 1–7.

Wang, K., Guo, H., Ma, Q., Su, W., Chen, L., & Zhu, D. (2018). A portable and automatic Xtion-based measurement system for pig body size. *Computers and Electronics in Agriculture*, 148: 291–298.

Zaragoza, L.E.O. (2009). Evaluation of the accuracy of simple body measurements for live weight prediction in growing-finishing pigs. MSc. Diss. Univ. of Illinois, Urbana, Illinois.

Predicting tail biting and diarrhea amongst growing pigs from drinking patterns: An evaluation of the predictive performances of volume and drinking frequencies

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Abstract

Based on changes in their drinking patterns, predictions of tail biting and diarrhea amongst growing pigs were generated and evaluated. A spatial, multivariate dynamic linear model was used to model simultaneously monitored drinking patterns across multiple pens in a section of weaners, and across multiple pens in a section of finishers.

Both volume (litres/hour) and frequency (bouts/hour) were monitored and modelled. The predictive performances of the two sets of data were evaluated separately for both weaners and finishers using a two-sided tabular CUSUM. Time windows, including 24 hours and 48 hours before the day of the event, were applied and the predictive performances were reported as *Area Under the ROC Curve* (AUC).

Generally, the predictive performances were high for both volume and frequency (Tail biting finishers: AUC = 0.79 – 0.88, Tail biting weaners: AUC = 0.89 – 0.92). For finishers (30-110 kg), frequency (bouts/hour) was a better predictor of outbreaks of both tail biting and diarrhea as well as either of the events given either time window. For weaners (7- 30 kg), however, the performances for predicting tail biting were equally high for volume and frequency given either length of the time window. For the prediction of diarrhea or either of the events, the performances were also close to equal between volume (litres/hour) and frequency (bouts/hour) but they differed between the two lengths of time windows.

In conclusion, frequency tends to be a better predictor of events amongst finishers, whereas the differences in predictive performances between volume and frequency were less distinct amongst weaners.

Keywords: dynamic linear model, multivariate, drinking volume, drinking frequency, tail biting, prediction

Introduction

It is well described in the scientific literature how changes in pigs' drinking patterns can be modelled using dynamic linear models (DLM's) in order to predict outbreaks of unwanted events like diarrhea, pen fouling and tail biting (Madsen *et al.,* 2005; Jensen *et al.,* 2017; Dominiak *et al.,* 2018b).

Traditionally it is the volume of water (litres/hour) passing a water meter which is modelled and interpreted as an expression of pigs' drinking activity. The monitored volume can, however, consist of a combination of fewer, longer periods of pigs drinking, as well as multiple, frequent activations of the drinking nipple (bouts) without an actual drinking behavior. An increase in the activation frequency (bouts/hour) of the drinking nipple can reflect an increased activity level, or increased explorative behavior, which is hypothesized to proceed outbreaks of tail biting (Larsen *et al.,* 2016) as well as outbreaks of diseases, like diarrhea, or unwanted behavioural changes, like pen fouling (Dominiak, 2017).

In the present study, both volume (litres/hour) and frequency of drinking nipple activations (bouts/hour) are monitored and modelled separately in a *spatial multivariate dynamic linear model* (DLM) with the intent to predict outbreaks of tail biting, diarrhea or either of the two events in specific pens in a section of weaners (7-30 kg) and in a section of finishers (30-110 kg).

The objective of the paper is to evaluate the performance of drinking volume and of drinking frequency as predictors of outbreaks of unwanted events.

Methods and materials

Experimental data

The model, which is applied in this paper, was originally developed on water data (litres/hour) from two different herds (a weaner herd and a finisher herd). It is able to model simultaneously monitored data from multiple pens in multiple sections of a herd of growing pigs (Dominiak *et al.*, 2018a) in order to identify the specific area (pen or section) where an outbreak of an unwanted event is going to occur within the next 24 or 48 hours (Dominiak *et al.,* 2018b).

In the present study, the model is applied to data from a third herd, which includes only one section of weaners and one section of finishers, thus aiming to predict an outbreak in a specific pen within the modelled section. The model is applied separately to two data sets from the weaner section (litres/hour and bouts/hour) and separately to two data sets from the finisher section (litres/hour and bouts/hour).

In the weaner section, a total of eight pens are monitored, whereas a total of 16 pens are monitored in the finisher section. Both volume (litres/hour) and drinking frequency (bouts/hour) are obtained at the same time using the same photo-electric flow sensors (RS V8189 15 mm Dia. Pipe). Each sensor is placed on the water pipe supplying two neighbouring pens (one double pen) with water, thus monitoring four time series (four double pens) from the weaner section and eight time series (eight double pens) from the finisher section. The monitored pens are evenly distributed on both sides of a central aisle in both sections. One double pen of weaners contains a total of 80 pigs, whereas one double pen of finishers contains a total of 40 pigs. The data is monitored across six batches from September 2015 to March 2017 (finishers) and to November 2017 (weaners). Data was obtained whilst a project on tail biting was conducted in the herd. Therefore, 50% of the pens in a section contains pigs with intact tails and 50% of the pens contains pigs with docked tails. In Batches 1, 3, and 5 the pigs with intact tails were in pens on the left side of the aisle and the pigs with docked tails on the right side. In Batches 2, 4, and 6 the pigs with intact tails were on the right side and the docked pigs on the left side of the aisle.

Every morning, the caretakers in the herd registered events of diarrhea and tail bites according to a project protocol (Lyderik *et al.*, 2016). These event registrations constitute the gold standard in the evaluation of the predictive performance.

General model

Each data set (litres/hour and bouts/hour for weaners, litres/hour and bouts/hour finishers) is modelled separately using the same dynamic linear model. Both types of variable (of litres or bouts) monitored over time is modelled simultaneously for all sensors in the relevant section using a multivariate dynamic linear model (DLM) as described by West & Harrison (1999). The observation vector, $Y_t = (Y_{1t},\ldots,Y_{nt})'$, is the monitored variable per hour at time t for each of the n sensors. The relation between Y_t and the underlying parameter vector $\boldsymbol{\theta}_t$ at time *t*, as well as the evolution of the system over time, is described through an observation equation and a system equation (Equations (1) and (2), respectively):

$$Y_t = \mathbf{F}'_t\theta_t + \nu_t, \qquad \nu_t \sim N(\mathbf{0}, \mathbf{V}_t), \tag{1}$$

$$\theta_t = \mathbf{G}'_t\theta_{t-1} + \omega_t, \qquad \omega_t \sim N(\mathbf{0}, \mathbf{W}_t), \tag{2}$$

The aim of the DLM is to predict the next observation. That is to estimate the parameter vectors, $\theta_1, \ldots, \theta_t$, from the observations, $Y_1, \ldots, Y_t$. Through every hourly observation of the variable, the model learns more of the general pattern, and it is constantly updating the amount of information adding the newest observation. Any difference between the predicted observation and the actual observation is contained in the two error terms, V_t and W_t. If the pigs follow their normal pattern and drink, or activate the drinking nipple as much as expected, the prediction of the next observation is close to perfect, and any prediction error will be small. If, on the other hand, something is causing the pigs to change their pattern, the prediction error will be larger. A systematic change in the normal pattern will generate a sequence of larger prediction errors, and this will lead to an alarm, which is generated by a *two-sided tabular CUSUM* as described by Montgomery (2013).

Modelling diurnal patterns

Both litres/hour and bouts/hour for weaners and finishers show a clear diurnal pattern, which can be described in a super-positioned DLM consisting of three harmonic waves and a linear growth trend as shown by Madsen *et al.* (2005) and Dominiak *et al.* (2018a). Each harmonic wave is expressed as a cyclic model in the DLM through the trigonometric *Fourier form representation of seasonality* (West & Harrison, 1999) as shown in Equation (3). The Fourier form describes a harmonic wave for any frequency, $\omega \in (0,\pi)$, with $\omega = \pi/24$ yielding a wave with a period of 24, $\omega = 2\pi/24$ yielding a wave with a period of 12, and $\omega = 3\pi/24$ yielding a wave with a period of 8.

$$F_t^h = \begin{pmatrix} 1 \\ 0 \end{pmatrix} \qquad \text{and} \qquad G_t^h = \begin{pmatrix} \cos(\omega) & \text{Sin}(\omega) \\ -\cos(\omega) & \text{Sin}(\omega) \end{pmatrix} \tag{3}$$

The linear growth trend, which describes the underlying level and trend of pigs drinking more water as they grow, is expressed as a DLM as shown in Equation (4):

$$F_t^l = \begin{pmatrix} 1 \\ 0 \end{pmatrix} \qquad \text{and} \qquad G_t^l = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix} \tag{4}$$

Modelling spatial structure

The spatial structure enables the model to identify a specific pen within a section, where the pattern has changed systematically, and an alarm is then generated for that specific area, hereby directing the managerial focus thereto. In the present model, a spatial structure is incorporated by allowing for interactions between sensors (the modelled variables) through direct modelling of the interactions in the design and system matrices as well as by estimating full variance-covariance matrices.

All variances components are estimated by the *Nelder-Mead* algorithm in the statistical software R (R Core Team, 2017). The observation variances, V_t, are estimated directly, whereas a system-variances, W_t, for each of the four models are estimated through discount factors as described in Dominiak *et al.* (2018a).

Evaluation

For both volume and frequency, weaners and finishers, the model is trained on learning data (four batches, 66%) and tested on test data (two batches, 33%) with no pigs delivering data to both data subsets. The generation of alarms from systematical changes in the drinking patterns is done using a two-sided tabular CUSUM, as described by Montgomery

(2013). The standardised cumulated sums (CUSUMs) of the positive prediction errors and of the negative prediction errors are plotted over time, and if either sum exceeds a defined threshold, an alarm is generated.

An event is registered by the personnel in the morning, which is once per 24 hours. The alarms can, however, be generated at an hourly basis because the model updates with an observation every hour. Therefore, two time windows, lasting from 24 hours and 48 hours before an event until the end of the day where the event is registered, are defined according to Dominiak *et al.* (2018b). All alarms within a time window are considered as one true positive (TP) alarm. If no alarms are generated within a time window, it is considered false negative (FN), whereas single days with alarms but no events are false positive (FP) and single days without alarms but with events are false negative (FN) (see Figure 1).

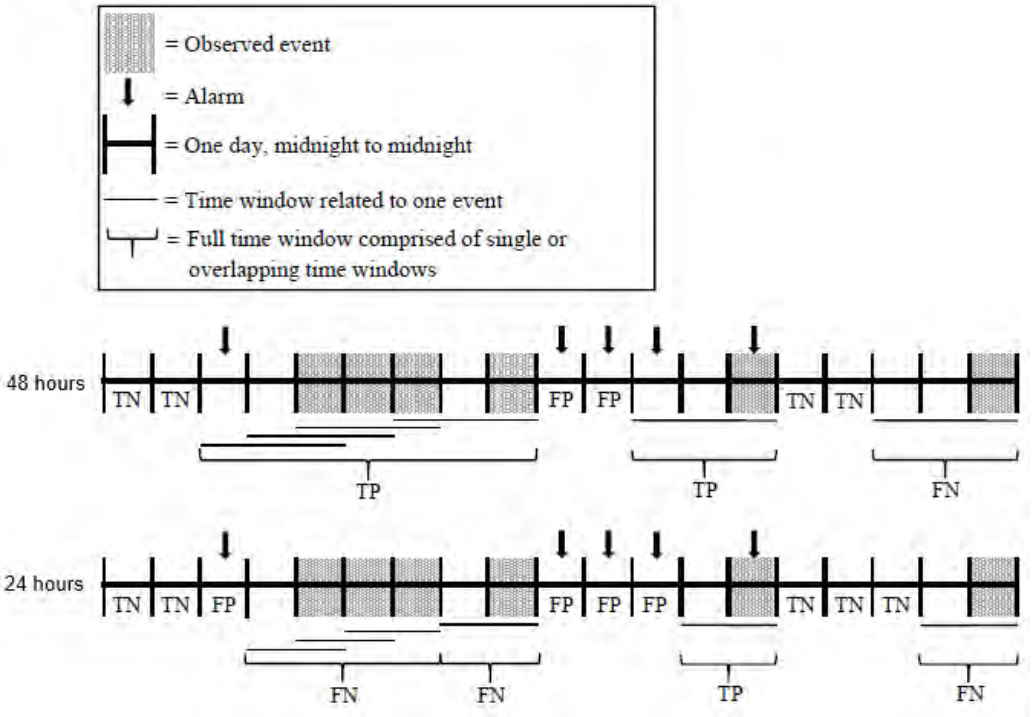

Figure 1. Illustration of time windows as described by Dominiak *et al.* (2018b) with TP, TN, FP and FN alarms defined as described in the text

Based on the categorisation of the alarms, the model performances are measured by the conditional probabilities, *sensitivity* and *specificity*, and the *areas under the ROC curve* (AUC) are calculated.

Results and discussion

Weaners

The predictive performances of both volume and frequency for the two defined time windows and each type of event amongst weaners are shown in Figure 2.

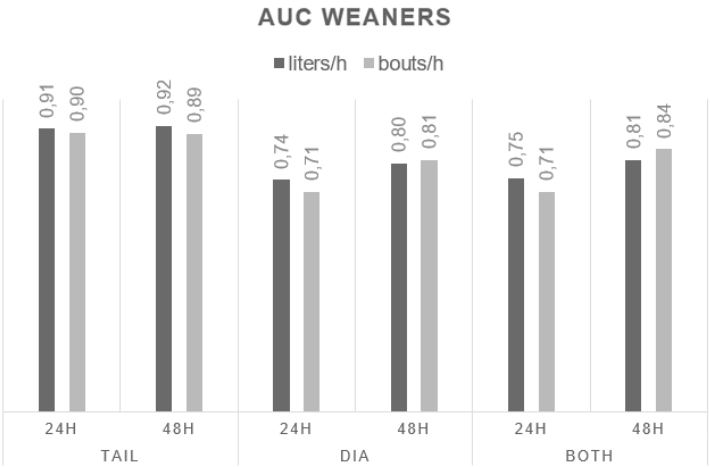

Figure 2. The AUC for the prediction of outbreaks of tail bites (Tail), diarrhea (Dia), or either of the two events (Both) in a specific pen of weaners based on volume (litres/h – dark grey bars) or drinking frequency (bouts/h light grey bars). Results are shown for each of the two time windows starting 24 hours and 48 hours before the day of the event

The results for weaners indicate that volume and frequency are equally good predictors of outbreaks of tail bites, diarrhea or either of the events. Looking at the shorter time window (24 hours), volume yields a slightly better performance than frequency for all event types, suggesting that the weaner pigs drink more water (or activate the drinking nipples for longer time) just prior to an event. It is also seen that the performances for predicting outbreaks of tail biting alone are higher than for the other types of events for both volume and frequency. These impressive results (AUC from 0.89–0.92) for prediction of tail bites may reflect a relatively high prevalence of tail biting events due to 50% of the pigs having intact tails. Despite this possible cause of very high performances, the results in general show very high predictive performances for both volume and frequency in the weaner data, and it can be concluded that the use of this spatial, multivariate DLM for the modelling pigs' drinking patterns is successful for predicting unwanted events amongst weaner pigs when applied to both volume data (litres/hour) and frequency data (bouts/hour).

Finishers

The predictive performances of both volume and frequency for the two defined time windows and each type of event amongst finishers are shown in Figure 3.

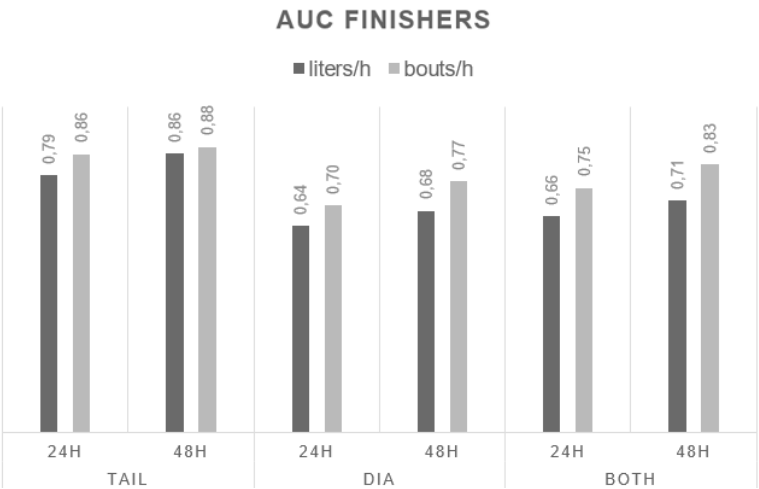

Figure 3. The AUC for the prediction of outbreaks of tail bites (Tail), diarrhea (Dia), or either of the two events (Both) in a specific pen of finishers based on volume (litres/h – dark grey bars) or drinking frequency (bouts/h light grey bars). Results are shown for each of the two time windows starting 24 hours and 48 hours before the day of the event

The results for finishers show that frequency consistently is a better predictor of outbreaks of tail bites, diarrhea or either of the events than volume given either length of time windows. These results indicate that finisher pigs increase their activity level, expressed as their exploratory or manipulative behaviour towards the drinking nipple, but not the amount of water they drink, prior to an outbreak of tail biting or diarrhea. An increase in explorative behaviour preceding outbreaks of tail bites, has also been described by Statham (2008). In general, finisher pigs tend to be less active than weaner pigs (Dominiak, 2017), and an increased activity may reflect a disturbance, or state of stress, in the pen which cause the pigs to be restless.

Generally, the predictive performances of both volume and frequency are lower for the finisher pigs than for the weaner pigs. The highest performances are obtained for bouts and litres predicting tail biting within the 48 hours' time window (AUC = 0.88 and 0.86), as well as for bouts predicting tail biting within the 24 hours' time window (AUC = 0.86). Overall it can be concluded for the finisher data as well, that the use of this spatial, multivariate DLM for modelling pigs' drinking patterns is successful for predicting unwanted events amongst finisher pigs when applied to both volume data (litres/hour) and frequency data (bouts/hour).

Conclusions

Drinking frequency (bouts/hour) show a tendency to perform better than drinking volume (litres/hour) for predicting outbreaks of unwanted events amongst finisher pigs, whereas no such difference was found for the prediction of outbreaks amongst weaner pigs.

The results of this study indicate that finisher pigs increase their activity level, expressed as an explorative or manipulative behaviour towards the drinking nipple, but not their drinking behaviour, prior to an outbreak of tail biting or diarrhea. This may reflect an increase in the stress level of the finisher pigs. Further studies should, however, be conducted in this area in order to determine which is the better predictor of the two variables with certainty.

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References

Dominiak, K.N. (2017). *Spatial modeling of drinking patterns as a tool for reducing alarms in pig production*, PhD thesis, Graduate School of Health and Medical Sciences, University of Copenhagen.

Dominiak, K.N., L.J. Pedersen and A.R. Kristensen. (2018a). Spatial modeling of pigs' drinking patterns as an alarm reducing method I. Developing a multivariate dynamic linear model. *Computers and Electronics in Agriculture*, https://doi.org/10.1016/j.compag.2018.06.032.

Dominiak, K.N., J. Hindsborg, L.J. Pedersen and A.R. Kristensen. (2018b). Spatial modeling of pigs' drinking patterns as an alarm reducing method II. Application of a multivariate dynamic linear model. *Computers and Electronics in Agriculture*, https://doi.org/10.1016/j.compag.2018.10.037.

Jensen, D.B., N. Toft and A.R. Kristensen (2017). A multivariate dynamic linear model for early warnings of diarrhea and pen fouling in slaughter pigs. *Computers and Electronics in Agriculture,* 135: 51–62.

Larsen, M.L.V., H. M-L. Andersen, L.J. Pedersen. (2016). Can tail damage outbreaks in the pig be predicted by behavioural change? *The Veterinary Journal*, 209: 50–56.

Lyderik, K.K., H. M-L. Andersen, H.H. Kristensen and L.J. Pedersen. (2016). *Protocol for daily observations in the herds of the PigIT project.* PigIT Report no 8. www.pigit.net

Montgomery, D.C. (2013). *Statistical Quality Control A Modern Introduction*, 7th edition, John Wiley & Sons Inc.

R Core Team (2017). R: A language and environment for statistical computing. *R Foundation for Statistical Computing*, Vienna, Austria.

Statham, P. (2008). *Effects of experience and individuality on tail-biting in pigs.* PhD thesis, University of Bristol.

West, M. and Harrison, J. (1999). *Bayesian Forecasting and Dynamic Models*, 2nd edition, New York, USA: *Springer*, 680 pp.

Relationship between automatic records of pig respiratory distress on farm and the prevalence of lung lesions at slaughter

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Abstract

Worldwide the pig industry continues to suffer substantial financial losses due to respiratory disease, and this is also the main reason for antimicrobial use in growing-finishing pigs in Ireland. The Pig Respiratory Distress package (SOMO) performs continuous and automated measurements of cough sounds, issuing a Respiratory Distress Index (RDI; average number of coughs/pig-day).

The objective of this study was to assess the relationship between SOMO measurements and the prevalence of lung lesions at slaughter.

SOMOs were placed in eight rooms, each with six pens (196 ± 4.6 pigs/room), on a commercial farm with a history of respiratory disease. A total of 1,573 pigs from four consecutive batches were monitored from 25 ± 5.3kg to slaughter, 114 ± 15.4kg, when their lungs were individually scored for pneumonia, scarring and pleurisy lesions. The relationship between lung lesions and weekly RDI was assessed using Spearman's rank correlation with room as the experimental unit.

Results showed that the RDI during the last four weeks of the finisher stage was strongly correlated with the prevalence of pneumonia ($r_s = 0.72$; $r_s = 0.82$; $r_{s =} 0.89$ and $r_{s =} 0.79$, $P < 0.05$) and scarring ($r_s = 0.72$; $r_s = 0.82$; $r_{s =} 0.89$ and $r_s = 0.79$, $P < 0.05$) lesions. Even though the SOMOs are calibrated to raise an alert when RDI is ≥10, RDIs obtained in our study suggest that levels of coughing lower than expected (RDI ≥ 2 vs RDI ≥ 10) were also indicative of on-farm respiratory disease.

In conclusion, the SOMO boxes could play a role in identifying respiratory disease in finisher pigs. However, a better understanding of the baseline coughing frequency in healthy pigs is needed.

Keywords: Coughing, lung lesions, PLF, porcine respiratory disease complex

Introduction

Worldwide, the pig industry continues to suffer substantial economic losses due to respiratory disease (Nathues *et al.*, 2017). These losses are related to decreased growth and increased mortality, condemnations at slaughter, and increased costs for treatments, vaccination and labour (Zimmerman *et al.*, 2012). Respiratory disease is also associated with welfare problems due to the associated pain and discomfort and reduced ability to compete for resources.

Furthermore, respiratory disease is the main reason for antimicrobial (AM) use in growing and finishing pigs in Ireland (Pereira do Vale, unpublished data). Although AM use in the treatment of disease is of vital importance to maintaining pig health and welfare, mis- and over use of AM is contributing to antimicrobial resistance (Lhermie *et al.*, 2017). Prudent AM use in pig production can be achieved through improved housing and husbandry of

pigs, stricter biosecurity practices and vaccination programmes combined with early and precise diagnosis (Postma *et al.*, 2016, 2015).

Precision technologies are playing an increasingly important role in the early diagnosis of disease in intensive production systems (Norton & Berckmans, 2018). The Pig Respiratory Distress Package (SOMO) performs continuous, 24/7, automated measurement of porcine respiratory health through sound analysis (Hemeryck *et al.*, 2015). It was developed to give farmers an objective measure of pig cough occurrence throughout the entire farm. By detecting respiratory problems at an early stage, improvements in animal health and welfare and a reduction of AM use are likely to be achieved (Vandermeulen *et al.*, 2013). Meat inspection data can also play an important role in informing herd health and welfare plans (Harley *et al.*, 2012, 2014). Precision technology when combined with information on lung pathologies from slaughterhouse checks (Van Staaveren *et al.*, 2016; Costa, 2018) has the potential to provide a complete picture of a farm's respiratory health status. However, it is not known how pathologies identified post-mortem relate to coughing on farm. The objective of this study was to assess the relationship between SOMO measurements and the prevalence of lung lesions at slaughter.

Material and methods

This study took place on a commercial farm with a wean-to-finish system from July to November 2018. The farm was selected due to its history of respiratory disease (Costa, 2018). Pigs were housed in rooms divided in six fully (concrete) slatted pens, each holding c. 36 pigs. Water was provided *ad libitum* and pigs were fed three times per day, (Hydromix wet feeding system, Big Dutchman, IDS, Portlaoise, Co. Laois, Ireland). In the weaner and grower accommodation there was an automatic temperature control system in place with fans in the ceiling (Big Dutchman). The finisher facilities were naturally ventilated. The rooms were artificially illuminated from 08.00 to17.00 h.

Over a six-week period, four batches of pigs (1,573 in total) of approximately 12 weeks of age and weighing 25 ± 5.3 kg were housed in eight rooms (mean number pigs per room 197 ± 4.6) on arrival at the farm. All pigs were ear-tagged with different numbers and colour tags per pig and batch on arrival at the farm following a 90 km journey from the breeding unit. Pigs were followed for 13 weeks, until reaching the targeted slaughter weight of 110 kg (mean 114 ± 15.4 kg). Every batch was followed on transfer between the three different production stages (weaner, grower and finisher accommodation). Group composition was not changed (i.e. there was no re-mixing) between stages.

Pig Respiratory Distress Package

The SOMO (SoundTalks NV, Ambachtenlaan 1, 3001 Leuven, Belgium) performs continuous and automated measurements of cough sounds, issuing a Respiratory Distress Index (RDI; average number of coughs per pig per 24 hours). It also records temperature and relative humidity. SOMO boxes were installed, following manufacturer guidelines (i.e. microphone placed in the centre of each room at a height ≥ 2 m and covering a maximum radius of 8.5 m). In this way there was 100% coverage of the weaner and grower accommodation and 99.2% coverage of the finisher houses. Two temperature and one relative humidity sensors were also installed in each room. The SOMO boxes were moved with the pigs through the different production stages. All data were stored and could be accessed using the SOMO associated pig respiratory distress monitoring (RDM) software.

Slaughterhouse checks

Pigs were sent to the slaughterhouse in eight groups, corresponding to the eight rooms monitored with the SOMO boxes. The same veterinarian/the first author carried out all lung examinations.

For each pig, lung lobes were scored for pneumonia lesions using the method described by Madec & Derrien (1981). The scores were 0 (no pneumonia), 1 (1 – 25% of the lung lobe affected), 2 (26 – 50%), 3 (51 – 75%) and 4 (76 – 100%). The overall surface affected was also estimated and it accounted for lobe weights, as per Christensen *et al.* (1999). Lung scars, defined as healed pneumonia lesions, were recorded as absent (0) or present (1).

Pleurisy was scored on the dorsocaudal (DC) lobes using a modified version of the Slaughterhouse Pleurisy Evaluation System (SPES) (Dottori *et al.*, 2007). The scores were 0 (no pleurisy), 2 (focal lesions in one lobe), 3 (bilateral adhesions or monolateral adhesions affecting more than 1/3 of the diaphragmatic lobe), and 4 (extensive lesions affecting more than 1/3 of both diaphragmatic lobes). Cranial pleurisy (adhesions between the surface of the apical and cardiac lobe, and/or adhesions between the lung and the heart) was recorded as absent (0) or present (1).

Statistical analysis

All analyses were performed in R version 3.5.1 (R Core Team, 2018). Spearman's rank correlation was performed using room as the experimental unit. Overall, the dependent variables used for statistical analysis were pneumonia-related variables: prevalence of pneumonia (Madec scores ≥ 1) and scars; pleurisy-related variables: the prevalence of dorsocaudal (SPES ≥ 2) and cranial pleurisy; whereas the independent variables corresponded to median RDI values for each week the trial pigs were followed.

Results and discussion

Figure 1 shows the evolution of the respiratory distress index (RDI), as a function of time and production stage, measured in eight rooms. In general, RDIs were highest during the first days in the weaner production stage. This could be related to the stress associated with transport from the breeding to the grower/finisher unit, remixing and the subsequent adaptation to the new social group, environment and feed (Peden *et al.*, 2018). In the grower accommodation, the RDI generally decreased and remained somewhat constant. RDIs increased in five of the eight rooms towards the end of the finisher stage.

A total of 1,540 lungs were assessed at slaughter. On average, each room had 193 ± 5 lungs assessed (range 185 – 199). The prevalence of pneumonia, dorsocaudal and cranial pleurisy and scars and the associated RDI for each of the eight rooms is presented in Table 1. Rooms with the highest prevalence of pneumonia and scar lesions had the highest median RDI values (~1) for the whole period. These were also the rooms in which the highest levels of coughing were recorded throughout most of the seven weeks of the finisher stage (Figure 1).

However, despite the high prevalence of lesions in several of the rooms, an RDI greater than 10 was only recorded in room seven. For RDIs ≥ 10, the SOMO box sounds an alarm (sending a text message or email to the farmer) indicating that pigs housed in that compartment are coughing above the threshold considered a normal level by the manufacturer. This suggests that a lower threshold for sounding an alarm would be appropriate. Indeed, Hemeryck *et al.* (2015) reported a 48% prevalence of pneumonia lesions and a 12% prevalence of pleurisy with a corresponding RDI of ≈ 10 on two occasions during the finisher stage.

The univariable analysis of the respiratory distress index for each week of the different production stages and the four lung lesion categories is presented in Figure 2.

There were no statistically significant correlations between RDI values in the weaner stage (weeks 12 and 13) and lung lesions at slaughter ($P > 0.05$). Lung lesions in slaughter age pigs are not good indicators of respiratory disease affecting younger pigs, because of the ability of lesions to heal without scarring (Pagot *et al.*, 2007; Straw *et al.*, 1990; VanAlstine,

2012). Thus, we cannot discard the potential presence of respiratory disease in the weaner stage or the usefulness of the cough monitors in detecting it. To validate the effectiveness of cough monitors in predicting respiratory disease outbreaks in weaner pigs, *post mortem* examinations of weaners showing signs of respiratory disease (higher levels of RDI) should be performed and include monitoring the presence of common respiratory pathogens over time.

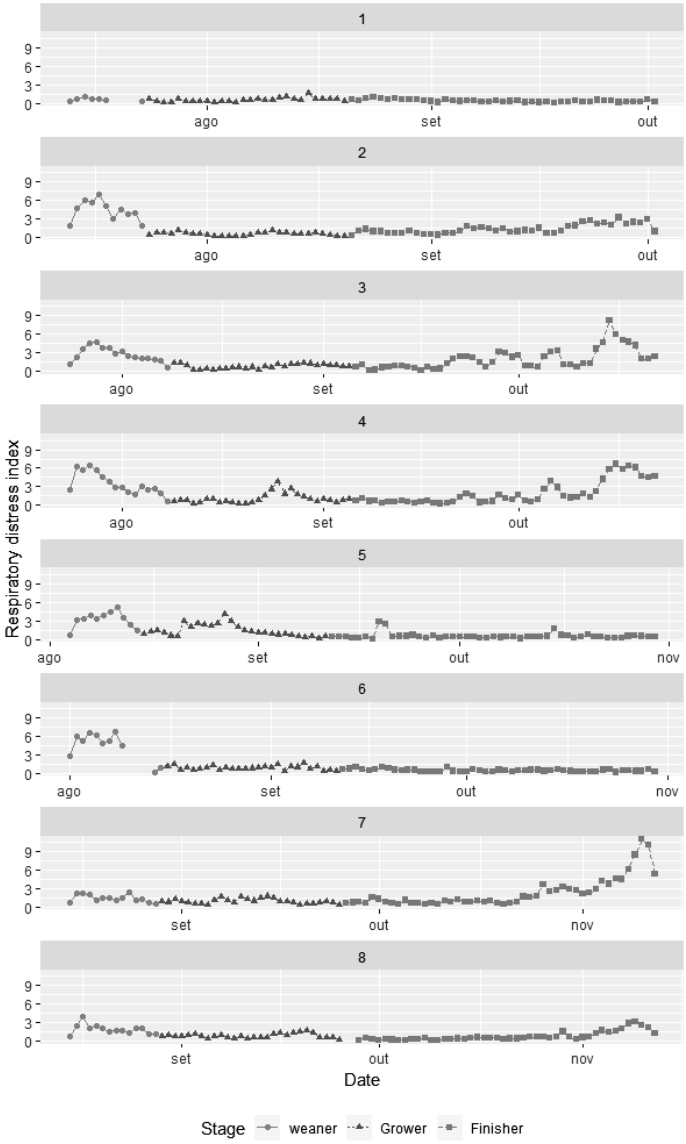

Figure 1. Respiratory distress index as a function of time and production stage for eight rooms (labelled from 1-8)

Table 1. Prevalence (%) of lung lesions assessed at slaughter for rooms 1 - 8 and corresponding overall median, minimum and maximum values of respiratory distress index (RDI)

Room	Pneumonia (%)	Dorsocaudal Pleurisy (%)	Cranial Pleurisy (%)	Scars (%)	Overall Median RDI	Min RDI	Max RDI
1	6	11	19	9	0.36	0.07	1.63
2	23	17	22	21	0.91	0.08	6.98
3	43	18	19	24	1.15	0.09	8.28
4	42	18	24	24	1.13	0.25	6.64
5	6	3	8	13	0.49	0.07	5.20
6	7	8	8	9	0.53	0.10	6.76
7	38	10	13	24	1.05	0.28	10.98
8	7	10	15	13	0.68	0.15	4.05

There were some statistically significant correlations between RDI and lung lesions during the grower stage (weeks 14–17). Indeed, the only association between RDI and dorsocaudal pleurisy was found on week 17 ($P = 0.027$). This and the negative correlations found with dorsocaudal pleurisy ($P = 0.016$) and cranial pleurisy ($P = 0.019$) on week 15 are difficult to explain from a biological point of view.

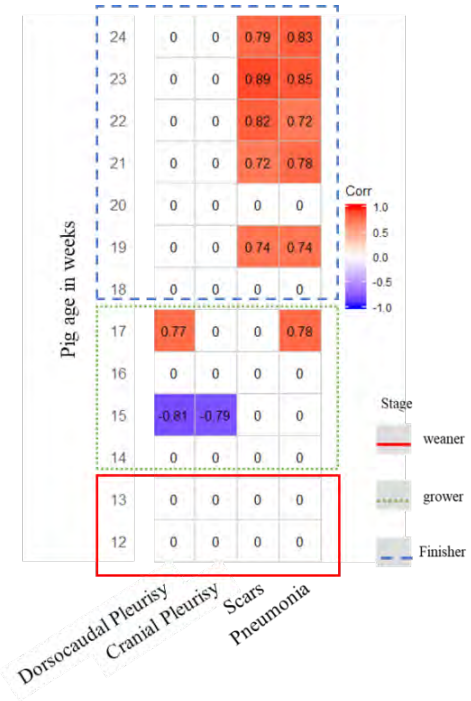

Figure 2. Spearman rank correlations between the respiratory distress index in function of pigs age in weeks. Cells with zeros correspond to non-significant results

Strong correlations were found between RDI values during finisher stage (weeks 18–24) and pneumonia (week 19: $P = 0.037$; week 21: $P = 0.043$; week 22: $P = 0.012$; week 23: $P = 0.008$; week 24: $P = 0.011$) and scar lesions (week 19: $P = 0.037$; week 21: $P = 0.023$; week 22: $P = 0.045$; week 23: $P = 0.003$; week 24: $P = 0.019$) . These findings are consistent with Pagot *et al.* (2007), who reported an association between age and increased pneumonia lesions at slaughter. These results also confirm the capacity of the SOMO box to detect respiratory disease in real-time, as the last four weeks of finisher stage present the highest levels of RDI for those rooms with a high prevalence of pneumonia and scar lesions (Figure 1).

Conclusions

Under the conditions of this study there was good association between lung pathologies recorded at slaughter and coughs recorded on farm by the SOMO respiratory distress package, particularly during the finisher stage. Coughing was recorded in the earlier production stages but was not reflected in lung lesions at slaughter indicating that further research is required to validate the SOMO package for use with weaner and grower (i.e. younger) pigs. Further studies are also needed to clarify differences in levels of coughing throughout production stages and to verify the baseline coughing frequency in healthy pigs.

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References

Christensen, G., Soarensen, V., & Mousing, J. (1999). Diseases of the respiratory system. In B. Straw, S. D'Allaire, W.M., & D.J. Taylor (Eds.), *Diseases of Swine* (pp. 913–940). Ames: Iowa University Press.

Costa, M. (2018). *Evaluation of current feeding and management practices in Irish pig production and future strategies for improvement*. Universitat Autònoma de Barcelona.

Dottori, M., Nigrelli, A.D., Merialdi, G., Gozio, S., Bonilauri, P., & Cominotti., F. (2007). Proposta di un nuovo sistema di punteggiatura delle pleuriti suine in sede di macellazione. La griglia S.P.E.S. (Slaughterhouse Pleuritis Evaluation System). *Large Animal Review*, 13: 161–165.

Harley, S., Boyle, L.A., O'Connell, N.E., More, S.J., Teixeira, D.L. and Hanlon, A. (2014). Docking the value of pigmeat? Prevalence and financial implications of welfare lesions in Irish slaughter pigs. *Animal Welfare,* 23: 275–285.

Harley, S., More, S., Boyle, L.A., O' Connell, N.E. and Hanlon, A. (2012). Good animal welfare makes economic sense: potential of swine abattoir meat inspection as a welfare surveillance tool. *Irish Veterinary Journal,* 65:11.

Hemeryck, M., Berckmans, D., Vranken, E., Tullo, E., Fontana, I., Guarino, M., & van Waterschoot, T. (2015). The Pig Cough Monitor in the EU-PLF project results and multimodal data analysis in two case studies. In *7th European Conference on Precision Livestock Farming (EC-PLF)* (pp. 147–155). Milan.

Lhermie, G., Gröhn, Y.T., & Raboisson, D. (2017). Addressing antimicrobial resistance: an overview of priority actions to prevent suboptimal antimicrobial use in food-animal production. *Frontiers in Microbiology*, 7, 2114.

Madec, F., & Derrien, M. (1981). Fréquence, intensité et localisation des lésions pulmonaires chez le porc charcutier: Résultats d'une premiére série d'observations en abattoir. In *Journées de la Recherche Porcine en France* (pp. 231–236).

Nathues, H., Alarcon, P., Rushton, J., Jolie, R., Fiebig, K., Jimenez, M., … Nathues, C. (2017). Cost of porcine reproductive and respiratory syndrome virus at individual farm level – An economic disease model. *Preventive Veterinary Medicine*, 142: 16–29.

Norton, T., & Berckmans, D. (2018). Precision Livestock Farming: The Future of Livestock Welfare

Monitoring and Management? Animal Welfare in a Changing World (2018): 130.

Pagot, E., Pommier, P., & Keïta, A. (2007). Relationship between growth during the fattening period and lung lesions at slaughter in swine. *Revue de Médecine Vétérinaire*, 158(5): 253–259.

Peden, R.S.E., Turner, S.P., Boyle, L.A., & Camerlink, I. (2018). The translation of animal welfare research into practice: The case of mixing aggression between pigs. *Applied Animal Behaviour Science*, 204: 1–9.

Pereira do Vale, A., Arguello, H., Manzanilla, E.G., & Leonard, F.C. (2014). Evaluation of management practices and health concerns in irish pig farms. Unpublished manuscript.

Postma, M., Backhans, A., Collineau, L., Loesken, S., Sjölund, M., Belloc, C., … Dewulf, J. (2016). Evaluation of the relationship between the biosecurity status, production parameters, herd characteristics and antimicrobial usage in farrow-to-finish pig production in four EU countries. *Porcine Health Management*, 2(1): 9.

Postma, M., Stärk, K.D.C., Sjölund, M., Backhans, A., Beilage, E.G., Lösken, S., … Dewulf, J. (2015). Alternatives to the use of antimicrobial agents in pig production: A multi-country expert-ranking of perceived effectiveness, feasibility and return on investment. *Preventive Veterinary Medicine*, 118(4): 457–466.

Straw, B.E., Shin, S.J., & Yeager, A.E. (1990). Effect of pneumonia on growth rate and feed efficiency of minimal disease pigs exposed to actinobacillus pleuropneumoniae and mycoplasma hyopneumoniae. *Preventive Veterinary Medicine*, 9(4): 287–294.

VanAlstine, W.G. (2012). Respiratory system. In J.J. Zimmerman, L.A. Karriker, A. Ramirez, K.J. Schwartz, & G.W. Stevenson (Eds.), *Diseases of Swine* (10th Editi, pp. 348–363). Ames: Wiley-Blackwell.

Vandermeulen, J., Decré, W., Berckmans, D. Exadaktylos, V., Bahr, C., & Berckmans, D. (2013). The pig cough monitor: from research topic to commercial product. In 6th *European Conference on Precision Livestock Farming* (pp. 717–723). Leuven.

van Staaveren, N., Vale, A.P., Manzanilla, E.G., Teixeira, D.L., Leonard, F.C., Hanlon, A. and Boyle, L.A. (2016). Relationship between tail lesions and lung health in Irish slaughter pigs. *Preventative Veterinary Medicine*, 127: 21–26.

Zimmerman, J.J., Karriker, L.A., Ramirez, A., Schwartz, K.J., & Stevenson, G.W. (2012). *Diseases of Swine*. John Wiley & Sons, Inc.

Carcass quality traits of fattening pigs estimated using 3D image technology

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Abstract

The increasing demand for pig products, as world population increases, is inducing not only a shift to larger intensive pig farming systems, but also the need to optimise all aspects of pig production in order to achieve a profitable production. The value of pig carcass for meat production depends, primarily, on the carcass weight and on the relative proportions of fat and lean meat. This study focuses on the estimation of carcass traits for fattening pigs using image technology. An experiment with 80 pigs (Pietrain x Topigs 20) was performed in an experimental farm. Kinect® cameras were used to obtain 3D top-view images of live pigs during one week before slaughter while pigs were eating and an RFID system allowed the images to be matched with individual pigs. Several image features, such as lengths, areas and volumes were extracted to characterise the pigs' body. At slaughter, carcass traits were collected, such as slaughter weight, lean meat and back fat depth. Stepwise linear regression was used to determine which image features were relevant to estimate the different carcass traits. A dataset of 36 pigs was used as training set. Statistically relevant linear relations (*p-value* < 0.0005), exhibiting adjusted-R^2 ranging from 70–85%, were found between the image features and carcass traits. When applied to the 15 pigs used for validation, the performance decreased to the range of 50–60%. These results show the potential to estimate carcass traits of fattening pigs before being sent to slaughter from 3D image analysis.

Keywords: carcass quality, slaughter, stepwise linear regression, time-series

Introduction

As world population increases, the demand for pig products will increase. According to Eurostat, the EU produced 23.4 million tonnes of pig meat in 2017. This was over 1 million tonnes more than in the years 2012–2013. Also in 2017, there was a further rebound, + 8.3% in the real-term price of pigs, from the relative low value in 2015 (Eurostat, 2018). The value of a pig carcass for meat production depends, primarily, on the carcass weight and on the relative proportions of fat and lean. Estimates of these carcass traits during a pig's lifetime are invaluable for the pig breeder, as they allow specification of a performance target, management regime and genotype choice (Fisher *et al.*, 2003; Ruusunen *et al.*, 2012). Also, knowing how the pig is developing its carcass traits along the fattening period allows farmers taking action to manage them accordingly and get a higher income from each pig at slaughter (Einstein *et al.*, 2016). Costumer demands are becoming more specific, with carcass conformation playing an increasingly significant role in meat production industry.

There are several studies in which cameras are used to record images of pigs in a pen and estimate different image features. Some of them used 2D images to estimate lengths and areas to characterise the pig's body shape and link it, mainly, to weight (Kashiha *et al.*, 2014; Wongsriworaphon *et al.*, 2015). Also, studies in which 3D cameras were used, attempted to refine the previous ones by adding the depth information to improve pig's segmentation and volume estimations (Kongsro, 2014; Fernandes *et al.*, 2019). There are some studies in which the researchers tried to establish a link between these image

features and slaughter data. The works of Doeschl *et al.*, (2004) and Green *et al.*, (2005) are exhaustive studies attempting to show how 2D image features are related to different carcass traits at different stages of the fattening period, combining them in some cases with some external measurements, such as ultrasound measurements. In these works, the prediction properties of the regression models found achieved adjusted-R^2 values of 70%. Studies focusing more on the biological side of the carcass traits pointed out the high variability present in carcass composition when different breeds are considered and the high variety of aspects affecting it (Fisher *et al.*, 2003; Ruusunen *et al.*, 2012; Chen *et al.*, 2017). Thus, this should be taken into account when evaluating the performance and later application of the automated methods in practice.

The aim of this preliminary study is to define which image features are the best-correlated ones with the different slaughter variables and check if the time-evolution of these features over the fattening period improves these correlations.

Material and methods

Experimental data

The data are gathered during the performance of an experiment in a research facility in The Netherlands, with 80 pigs (Pietrain × Topigs 20), from which 51 pigs were selected to perform this study. The housing conditions were the typical for Dutch pig husbandry, according to the Dutch 'Integrale Keten Beheersing' (Integrated Chain Management) farm standards. The pigs were housed in four pens (each measuring 2.67 m × 6.26 m; 16.71 m^2, effective 16.14 m^2 , 0.81 m^2 per animal), each one equipped with a Schauer® electronic feeding station. All pigs had ad libitum access to feed and water during the whole experimental period. All pens had a partially slatted floor and were located in a climate-controlled room, based on the pigs thermoneutral zone. At slaughter, different variables were collected, such as slaughter weight or meat percentage, muscle and back fat thickness. In Table 1, a summary of the mean, median and standard deviation (*SD*) of these traits for all pigs monitored in the experiment (*N* = 51) are displayed.

Table 1. Mean, median and standard deviation (*SD*) of the slaughter variables for the 51 pigs monitored in the study. The slaughterhouse features are the final and slaughter weights, and percentages of meat, muscle and fat. The corrected yield (Yield) and start weight statistics of the pigs are also displayed in the table

N = 51	Start weight [kg]	Final weight [kg]	Slaughter weight [kg]	Meat [%]	Muscle [mm]	Fat [mm]	Yield [€]
Mean	30	109	86	59	65	13	137
Median	30	108	86	60	65	13	137
SD	3	5	4	2	5	3	7

A Kinect® camera was set above the feeding station to obtain 3D top-view images of live pigs one week before slaughter, while pigs were eating. An RFID system allowed the images recorded to be matched with each one of the 51 individual pigs monitored. Several image features, such as lengths, areas and volumes are extracted to characterise pig's body shape. In Figure 1, a schematic representation of some of the body features estimated is depicted. Moreover, in Table 2, the mean median and SD for this image features from the 51 pigs monitored are shown.

Table 2. Summary of mean, median and standard deviation (*SD*), in pixels, of the image features for the 51 pigs monitored (*N*), obtained directly from the image analysis of the 3D images gathered while pigs were eating during the last week of the fattening period

(*N* = 51)	*L1*	*L2*	*L3*	*L4*	*L5*	*L6*	*L7*	*A1*	*A2*	*A3*	*A4*	*HL1*	*HL3*	*HL5*	*avgH*	*maxH*
Mean	65	56	58	53	66	82	221	3,674	4,564	3,586	11,845	670	702	706	658	733
Median	65	56	58	53	66	82	222	3,659	4,535	3,570	11,868	673	707	708	663	734
SD	2	2	2	2	2	5	9	229	296	195	562	20	25	19	20	16

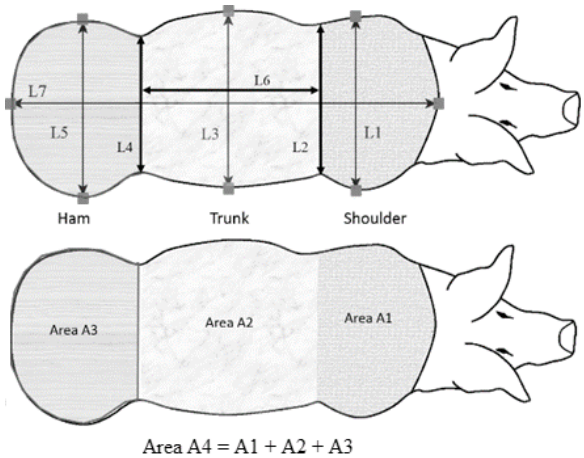

Figure 1. Schematic representation of the image features extracted directly from the image processing of the 3D images gathered when pigs visited the feeding station. Besides the ones depicted here, height and volume information is defined and tested too (based on a figure in Green *et al.*, 2005)

The height features, *HL1*, *HL3*, *HL5* are defined as the maximum height recorded in the line features *L1*, *L3* and *L5*, respectively. These heights, multiplied respectively by the areas, *A1*, *A2* and *A3*, define the volumes *V1*, *V2* and *V3*, respectively. Similarly to the total area (A4), the total volume is defined as the sum of the three previous volumes. The average (*avgH*) and maximal (*maxH*) height are defined as the average and maximum values obtained in the whole segmentation of the pig.

Data analysis

A stepwise linear regression, implemented in MATLAB® (The Mathworks™ Inc., 2015), was used to determine which image features are the best correlated ones to each specific slaughter variables. During the training process, coefficient of determination (R^2), the adjusted-R^2 and root mean square error (*RMSE*) were used to evaluate the performance. Besides, the parameter value estimations, its standard error, *p*-value and statistic *t*-test of these estimations were calculated. In the validation step, the coefficient of correlation (*r*), coefficient of determination (R^2) and statistical relevance, by means of the *p*-value, were evaluated.

Then, the time-evolution of these image features was used to evaluate the impact on the slaughter gathered data. In order to do so, two approaches are tested. Firstly, simply by linear fitting of this time evolution, the slope parameter was used as input for testing linear relations. This parameter is describing the rate of increase of that specific image

feature. Also, using the last week of data gathered for each image feature, a first order continuous-time time-invariant parameters transfer function model was used to model the evolution of the size of these features over the last week of the fattening period for each individual pig. This transfer function model is implemented using MATLAB® (The Mathworks, Inc., 2015b) Software and the CAPTAIN Toolbox (Young *et al.* 2007). The first order transfer function model has the following general structure,

$$y(t) = \frac{b_0}{s+a_1} u(t) + \xi(t) \quad [1]$$

where *y(t)* and *u(t)* are the output (image feature), and the input (binary input) of the model, respectively; ξ(t) is additive noise assumed to be zero mean, serially uncorrelated sequence of random variables with variance σ^2, accounting for measurement noise, modelling errors and effects of unmeasured inputs to the process; *t* is the sample of the measurement. The binary input (0-1) is just a step input to help define the dynamics present in the image feature time-evolution under study.

Some features defining the time evolution of these features can be extracted from these models, such as the time constant (*TC*) and the gain (*G*), defined as,

$$TC = \frac{1}{a_1} \quad [2]$$

$$G = \frac{b_0}{a_1} \quad [3]$$

The *TC* and *G* are evaluated and used as variables for the stepwise procedure instead of the value of the image feature itself. Also, combinations of both, image features and modelling features, are tested using its logarithm transformation as well.

Results and discussion

Firstly, a stepwise linear regression step is performed in order to evaluate which image features and/or modelling features are the best-correlated ones to each slaughter variable. It seems that for the slaughter data in relation to weight and yield, the median value of the image features from the last seven days of the fattening period are the best features to use as variables in the linear regression. However, for the slaughter variables in relation with the carcass quality, such as meat percentage and muscle and fat thickness, the time evolution of the image features is providing the best linear regression performances. Table 3 displays which image features are leading to the linear regression exhibiting the best linear regression results for the slaughter variables in relation to weight and yield. In Table 4, the results for the best linear regressions to estimate percentage of meat, muscle and fat thickness are displayed. Thus, the slaughter data related closely to the end of the fattening process, final and slaughter weights and yield, seems to be better correlated with the median of the last week measurements of these image features rather than with the features describing their time evolution.

On the other hand, the best linear regressions relations for carcass quality traits, such as meat, muscle and fat, are found when using the time-variant information extracted from monitoring the time evolution of the image features. Table 5 summarises the performance of these linear regressions in both training and validation steps. It can be seen that the best performance is for corrected yield (yield), final and slaughter weight. The performance for the carcass traits features it is worst. Among the latter ones, the best relation is achieved for the back fat depth. This may be related to the results in the study of Einstein *et al.*, (2016), in which it is shown that for some breeds the fat deposition rate is increasing towards the last part of the fattening period.

Table 3. Image features which are used as variables in a linear regression lead to the best performance in the estimation of yield, final and slaughter weights gather at the slaughterhouse. For these linear regressions, the coefficient estimates and their associated standard error (*SE*) is shown, together with *t*-test statistic and the *p*-value to define their statistical relevance. Median indicates that the median of the last seven days of the fattening period for each specific image feature is used as input in the linear regression

Corrected Yield				
Features [Median]	**Coeff. value**	**Coeff. SE**	**t-stat**	**p-value**
A1	0.0085	0.0042	2.03	0.0584
A3	0.064	0.015	4.27	0.0005
HL5	0.29	0.16	1.89	0.0768
maxH	-0.27	0.15	-1.80	0.0898
V2	1.1	0.5	2.14	0.0468
V3	-6.5	2.4	-2.71	0.0148
Final weight				
Features [Median]	**Coeff. value**	**Coeff. SE**	**t-stat**	**p-value**
L2	-0.94	0.42	-2.24	0.043
A3	0.05	0.01	3.89	0.002
HL1	-0.26	0.09	-2.83	0.014
HL5	0.32	0.10	3.36	0.005
V1	1.21	0.50	2.44	0.030
V2	1.15	0.39	2.91	0.012
V3	-5.83	1.78	-3.28	0.006
Slaughter weight				
Features [Median]	**Coeff. value**	**Coeff. SE**	**t-stat**	**p-value**
L7	-0.32	0.10	-3.31	0.004
A3	0.04	0.01	6.91	0.000
HL3	-0.06	0.03	-2.05	0.057
HL5	0.13	0.04	3.25	0.005
V1	1.33	0.31	4.24	0.001
V2	0.93	0.35	2.70	0.016
V3	-4.24	0.91	-4.66	0.0003

Table 4. Image time evolution features which are used as variables in a linear regression lead to the best performance in the estimation of carcass quality traits gather at the slaughterhouse. For these linear regressions, the coefficient estimates and their associated standard error (*SE*) is shown, together with *t*-test statistic and the *p*-value to define their statistical relevance. 'Gains' makes reference to use the gain from the transfer function modelling for that specific image feature as variable in the linear regression. 'Log Slope' indicates that the logarithm of the slope from a simple linear fit for the time evolution of the image feature is used as variable in the linear regression

Fat percentage				
Features [Gains]	**Coeff. value**	**Coeff. SE**	**t-stat**	**p-value**
L4	0.3238	0.0463	6.99	8.69E-07
HL1	0.0029	0.0014	2.00	0.059
avgH	0.0237	0.0022	10.60	1.17E-09
L4 : avgH	-0.0007	0.0001	-6.10	5.77E-06
Muscle percentage				
Features [Log Slope]	**Coeff. value**	**Coeff. SE**	**t-stat**	**p-value**
Intercept	217.64	39.50	5.51	0.0009
L5	9.02	4.33	2.08	0.0759
L6	8.68	3.21	2.71	0.0303
L7	28.66	6.90	4.16	0.0043
A1	-15.61	3.79	-4.12	0.0045
A2	-26.66	6.85	-3.89	0.0060
HL5	17.84	7.50	2.38	0.0490
avgH	-23.17	6.73	-3.44	0.0108
Muscle percentage				
Features [Log Slope]	**Coeff. value**	**Coeff. SE**	**t-stat**	**p-value**
Intercept	60.77	1.16	52.20	0.0000
L1	1.18	0.25	4.73	0.0089
L3	0.76	0.26	2.91	0.0437
L6	0.44	0.15	2.85	0.0465
A4	-0.0042	0.0014	-3.03	0.0386
HL1	-2.85	0.403	-7.08	0.0021
HL3	-0.39	0.07	-5.62	0.0049
avgH	0.73	0.16	4.61	0.0099
V2	-2.99	0.39	-7.68	0.0015

As the last seven days of the fattening period are used to estimate image features and their time evolution characteristics, it is expected that the best performance is obtained in relation to fat. When evaluating the percentage of meat and muscle size, the better correlations are found as the time evolution of the features is used. Moreover, these are

the only linear regressions in which the best performance is achieved when an intercept parameter is allowed. This may indicate the need for these relevant features to define this intercept parameter, for instance, their values at the beginning of the fattening period.

Table 5. Coefficient of determination (R^2), adjusted one (*adj-*R^2) and root mean square error (*RMSE*) of the linear regression in the training set and correlation coefficient (*r*), coefficient of determination (R^2) and statistical relevance (*p*-value) in the validation dataset for all the linear regressions selected as best and summarised in Tables 3 and 4 for each slaughterhouse variable

Slaughter variables	Training			Validation		
	R^2	adj-R^2	RMSE	r	R^2	p-value
Corrected Yield	0.74	0.67	3.84	0.87	0.67	0.00006
Final weight	0.76	0.65	2.75	0.82	0.61	0.00019
Slaughter weight	0.85	0.80	2.87	0.85	0.70	0.00005
Fat	0.74	0.67	2.87	0.89	0.55	0.00012
Muscle	0.68	0.51	2.87	0.69	0.26	0.0543
Meat	0.62	0.52	1.48	0.75	0.31	0.0504

In general, it seems that for the carcass traits to play a major role, the time evolution of the image features. Thus, it may be relevant to monitor the time evolution of these image features since the beginning of the fattening period. As stated in Einstein *et al.*, (2016), the meat percentage evolves non-linearly throughout the fattening period thus, evaluating how the image parameters are building up may be relevant to establish a trustworthy linear regression. Thus, studies using different pig breeds, together with monitoring of image features since the beginning of the fattening period and different housing conditions, are needed to prove several aspects. Firstly, to test if adding more refined time information improves the linear regression performances. Moreover, to test if the image features found as most relevant to the different slaughter variables in this study remain the same under these different conditions and/or breeds. Farmers could use such relations to estimate the profitability of each pig during the fattening process.

Conclusions

This paper explores the relation between image features representing fattening pigs' body shape and carcass quality traits, such as fat and muscle thickness or meat percentage. From these preliminary results, it seems that using the median value of different image features over the last seven days of the fattening period it is possible to estimate final weight, slaughter weight and corrected yield with an acceptable accuracy. In general, length, height, areas and volumes from the back part (ham) of the pig's body are better correlated to these slaughterhouse variables. However, the best linear regressions between image features and carcass traits are obtained when including time evolution information from the image features. Back fat thickness can be estimated using the gains, when the image features time evolution is modelled by transfer functions. Apparently, height information is relevant for fat thickness estimation. Besides, although exhibiting the worst performance, meat percentage and muscle thickness may be estimated by using the logarithm of the slope parameter characterising the time evolution of the image features

using linear fitting. It is expected that using image features time evolution throughout the fattening period, and not only from the last seven days of it, would improve the performance of the linear regressions for estimating carcass quality traits.

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References

Chen, G., Shui, S., Cai, Y., Na,L., and Su, Y. (2017). Production performance, slaughtering and pig qualityof different breed pigs. *Journal of Bioprocessing & Biotechniques*, 7(2): 1–7.

Doeschl, A.B., Green, D.M., Whittemore, C.T., Schofield, C.P., Fisher, A. V, Knap, P.W. (2004). The relationship between the body shape of living pigs and their carcass morphology and composition. *Animal Science*, 79: 73–83.

Einstein, M.E., Schinckel, A.P., Jungst, S., Booher, C., Newman, S. (2016). Evaluation of the Growth of Backfat Depth, Loin Depth, and Carcass Weight for Different Sire and Dam Lines. *The Professional Animal Scientist*, 25: 325–344.

Eurostat. (2018). Agriculture , forestry and fishery statistics 2018. *Statistical books*. Publications Office of the European Union, Luxembourg.

Fernandes, A.F.A., Dórea, J.R.R., Fitzgerald, R., Herring, W., Rosa, G.J.M. (2019). A novel automated system to acquire biometric and morphological measurements and predict body weight of pigs via 3D computer vision. *Journal of Animal Science*, 97: 496–508.

Fisher, A.V., Green, D.M., Whittemore, C.T., Wood, J.D., Schofield, C.P. (2003). Growth of carcass components and its relation with conformation in pigs of three types. *Meat Science*, 65: 639–650.

Green, D.M., Fisher, A.V., Carroll, S.M., Schofield, C.P., Whittemore, C.T., Doeschl-Wilson, A.B. (2005). The relationship between body dimensions of living pigs and their carcass composition. *Meat Science*, 70: 229–240.

Kashiha, M., Bahr, C., Ott, S., Moons, C.P., Niewold, T.A., Ödberg, F.O., Berckmans, D. (2014). Automatic weight estimation of individual pigs using image analysis. *Computers and electronics in Agriculture*, 107: 38–44.

Kongsro, J. (2014). Estimation of pig weight using a Microsoft Kinect prototype imaging system. *Computers and electronics in Agriculture,* 109: 32–35.

Ruusunen, M., Puolanne, E., Sevon-Aimonen, M.L., Partanen, K., Voutila, L., Niemi, J. (2012). Carcass and meat quality traits of four different pig crosses. *Meat Science*, 90: 543–547.

Young, P.C., Taylor, C.J., Tych, W., Pedregal, D.J. (2007). The Captain Toolbox. *Centre for Research on Environmental Systems and Statistics*, *Lancaster University, UK*. Internet: www.es.lancs.ac.uk/cres/captain.

Wongsriworaphon, A., Arnonkijpanich, B., Pathumnakul, S. (2015). An approach based on digital image analysis to estimate the live weights of pigs in farm environments. *Computers and Electronics in Agriculture*, 115: 26–33.

Session 13

Precision Livestock Farming Product Development, Opimisation and Testing in Field Conditions (2)

FAIRshare: Co-creating an online platform for the European farm advisory community to access and share digital advisory tools and services

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Abstract

The recent SCAR-AKIS policy brief on the Future of Farm Advisory Services (2017) recognises the opportunity for farm advisors to use new digital technologies and data flows to add value to their work through more open data exchange and digital services. It proposes the strengthening of those support systems which enable advisors to do their job more effectively; and improved connections for knowledge to be shared and developed further. The EU H2020 FAIRshare CSA project (www.h2020fairshare.eu) aims to enable a more digitally active farm and farm advisory community. As one aim of this project, a digital platform will be developed to collect and distribute information on digital tools and services used by advisors with a view to creating an inventory for the acquisition, exchange and dissemination of Digital Advisory Tools and Services (DATS). The overall goal is to establish a platform for the sharing of digital tools, experience and motivation within the farm adviser community and the farmers they serve. This will include a multi-lingual, web-based catalogue and semantic search tool, ('Digital Advisor') which itself takes digital services and tools for farmers and advisers as its core domain. The semantic tool will assist advisers in identifying best-matching digital tools and alternatives to address specific, user-defined farmer's challenges expressed in 'common search language'. This platform builds on components established in the VALERIE project (2017). It will incorporate a permanent networking facility to allow users of the platform to share experiences of using the tools and to facilitate potential collaboration in updating the tools for a wider audience of users. The initial experience from the development of this tool and implications of this online platform will be presented.

Keywords – Digital advisory tools, advisory services, digital services, digital technologies, digital agriculture

Introduction

Smart Farming(SF) in the form of smarter machines, Big Data, Internet of Things, ICT, sensors, and robotics amongst other technologies, are viewed as 'the future of agriculture' (Poppe *et al.*, 2015). Digitisation has the potential to transform the way farms are managed and operated. As agriculture becomes more digitised, farmers will be increasingly making decisions based on feedback from data on the farm (Wolfert *et al.*, 2017). SF applications will allow farmers to make more informed decisions, utilising targeted and precise information and knowledge that has been generated in real-time and in a local-specific context (Wolfert *et al.*, 2017). Most of the digital solutions that farmers use today are not complex IT systems, but more mainstream basic digital solutions (i.e. auto-steering, record keeping, yield mapping), while more complex variable rate applications of fertilizers, manure or irrigation are still at its early adoption stage (Fountas *et al.*, 2015). The time needed to work with SF technologies and the capacity-building required can impede the adoption of solutions by individual farmers rather than by advisors as evident in farmers surveys targeting SF Technologies since 2005 in Denmark and the USA: Fountas *et al.* (2005) to current farmers' surveys JRC (2019).

Many farmers who do not adopt SF technologies and digital tools have insufficient skills and competences (Adrian *et al.*, 2005; Pierpaoli *et al., 2013)*. Furthermore, the rural population in Europe is ageing rapidly with more than 55% of farm managers being above 55 years. This indicates a potential problem for the agricultural sector in terms of adoption rate of SF technologies because older farmers can have diminished incentives to change and less exposure to SF technologies (Eurostat, 2016). The role of farm advisors in the adoption of SF technologies is therefore crucial. Additionally, the precision farming software and services market is expected to be worth $1.77 billion by 2020 (Marketandmarkets, 2015) while the services segment is expected to portray a significant growth rate over the projected period, growing at a compound annual growth rate of 16.0% until 2025 (Grandview research, 2017).

As different supply chain actors undergo digital transformation, they will produce not only new tools, but potentially complete solutions. Consequently, farmers must use not just one platform, but several to get benefits from the digitization process. As a result, the digital transformation of agriculture rests not only with farmers, but also their business partners, including advisory services.

The digital divide from an advisor's perspective

Digital advisory tools and services (DATS), office, communications, analytical and digital farm management tools overlap, and share data and information. These interfaces for different analytical tools demonstrate the advantages of processing big data and making information available to multiple users. The cost of devices has reduced and most advisors use a laptop and/or smart phone/pad and a range of compatible software in their day to day work, yet many advisors don't have all the access, expertise or motivation that is needed.

Bespoke advisory tools are generally expensive in terms of development cost and ongoing support. Successful digital innovations, in terms of business case, benefit from a larger number of users as well as the individual user value. The principle of expanding the user audience is therefore crucial to longevity and reinvestment in upgrades. Some advisory tools have the advantage that they are built into farmer user systems with separate interfaces; here, the number of users is greater but the probability that all farmers use one system in an open market is low. In the absence of central co-ordinated web-based systems, DATS often rely on multiple outputs and protocols from different systems even in one geographic location. This increases cost and complexity.

Many advisors have overcome the high cost of bespoke systems by using freeware and particularly spreadsheets developed in house and shared between advisors. Some of these are quite elaborate, but all suffer from lack of version management and regular updates, as well as requiring a year-to-year entry of data. These are useful for smaller applications and as a development/proofing ground for professionally developed systems. Freeware also equips advisors with a limited but expanding range of good advisory tools, from mapping to messaging, technical support, governmental services, market information. These are capable of adding value to advisors' work. Many advisors are not using these to the full extent mainly because they do not know about them.

Materials and methodology

FAIRshare –will make digital advisory tools, **F**indable, **A**vailable, **I**nteroperable, **R**eusable and **Share**able. It has two main components:

The first component gathers the assessable knowledge base of the digital tools and services used by advisors by leveraging the networks of users and potential users (40,000 advisors in Europe) through an inventory/catalogue of tools and services, accessible

on an intuitively navigable online interface that has been co-designed with end users. Accompanying the tools in the online inventory will be information, for instance, short 'good practice' vignettes, on how the tools may be used/adapted for use. Secondly, FAIRshare will generate and resource a 'living laboratory', empowering advisor peers from across Europe to interact with the online inventory, in a series of workshops, to exchange, co-adapt, co-design and apply digital tools in a planned and strategic way. This paper focuses on the first component, which starts with a classification of digital advisory tools and the setting up of the repository of information on digital advisory tools and services.

The challenge for this project is to engage, enable and motivate the independent farm advisor community as multipliers and advocates for, creating a vibrant movement for farm advisory digital tools through sharing of tools, expertise and motivations. The approach is to support a multi-actor process that enables farm advisors, farmers and other AKIS actors to co-adapt existing advisory tools for expanded use and full exploitation. A further challenge is located at the interface between farmers and advisors, and relates to building the advisory capacities needed for managing data flows across regional, national and transnational AKISs. This involves the building of trust around issues such as big data and artificial intelligence through participatory approaches to co-designing communication and public engagement campaigns. This is to animate end users' interactions with a co-designed, intuitively navigable inventory of 'good tools' and 'good practices' that is representative of European and international (evolving) state-of-the-art. The SCAR-AKIS policy brief on the Future of Farm Advisory Services (2017) recognises this opportunity.

Motivating individual advisors to embrace the upcoming digital revolution starts with activities, tools, routines and services which are familiar and regularly used by both farmers and advisors. The digital revolution impacts can be seen everywhere and the spill-overs into agriculture mutually affect communications, access to information, advice and decision support tools and services. The major challenge is the integration of digital information, support services and farm data into day-to-day and strategic decision-making on farms.

Defining the scope of DATS

Within the broad range of digital tool used by advisors in their day to day work, it is difficult to define the scope of what should be included and how to anticipate the advisors demand or interest in looking for DATS and ultimately using them. It is clear to see that the scope should include communication, monitoring and analysis, decision support, regulation and quality control, quality assurance tools, teaching and learner support, organisation and management tools and services.

Digital communications tools: The mobile phone is the primary communication tool of the advisor and has become even more so with the development of better mobile coverage, cheaper phones and an acceptance that in modern society people are contactable 24/7 by voice or text and, more recently, video image. The phone is now a multifunctional device and low cost digital entry point for all ages. Smartphone invention proved a game changing technology for the agricultural sector and helped in increasing agricultural productivity and profitability in many ways. This was because farmers have direct access to valuable information timely and cheaply for i) conducting their farm operations better, ii) selling their crop production at higher prices and iii) using production inputs more efficiently. Many studies indicated those findings (Chhachlar & Hassan, 2013; Krone *et al.,* 2014; Jehan *et al.*, 2014). Web/app: These are a part of modern life with more and more everyday functions being completed over the internet. They also control over the entry and exit points for data and information from most digital systems. Radio/TV: Scheduled television and radio broadcasting has advanced significantly in recent years and is now enabled with

digital podcasts, video and live feed capability. Recent studies (Gorman *et al.,* 2017) show that for depth of penetration to rural community's local radio and agriculture, focused TV shows are still important and can be used effectively to influence hard to reach farmers (Kuta Yahaya & Badiru, 2002; Nazari, 2011).

Monitoring and analysis tools: Benchmarking can support farmers to improve their productivity and sustainability performance. Benchmarking is defined as improving the performance of a farm, for example, by comparing with peers, learning from others and identifying actions (EIP Agri Focus Group Final Report, 2017). Nutrient accounting systems at farm level are becoming more important and many agencies have set up benchmarking systems to allow farmers and their advisers monitor nutrient inputs from both farm productivity as well as compliance perspectives. Similarly, digital tools relying on Big Data are increasingly important at the farm level to reduce the use of agrichemicals for weed and disease control (Van Evert 2017[a,b]).

Decision support systems: Many decisions support system (DSS) digital tools involve a certain level of data collection and analysis of the current situation on the target farm, and then utilise this data to develop an action plan or options which can be evaluated to assist the farmer and his/her adviser in decision making (Poppe & Van Asseldonk, 2016),

Regulation and quality control and assurance tools: New digital tools are now commonplace within the EU and have exploited the advances in digital mapping and cloud-based animal movement systems, adding significantly to the efficiency of the EU Common Agriculture Policy (CAP) based farm subsidy and compliance checking. The evolution of access to these for both farmer and agent in the Farm Advisory Systems (FAS) has increased the efficiency of this administrative work.

Advisory services organisation and management: These are administrative tools which advisors use to record, report and analyse their own activity. They traditionally have been used for programme monitoring, client billing and other administrative purposes but now have advanced into customer relationship management systems (CRM), customer satisfaction dashboards and other useful management and administration tools.

Collecting the digital tool and service information

Building on the lessons learned in Smart-AKIS, a methodology and set of standards has been co-developed to perform a systematic review of DATS to feed the platform. Organisations and advisors using or supporting DATS will be invited to submit their tools to the FAIRshare platform, by filling in a questionnaire detailing the most important assessment criteria. The threshold for submitting DATS should be minimised to ensure a high level of participation from external DATS providers. Therefore, a conscious effort was made to keep the questionnaire concise and straightforward. A search strategy will also be developed to find DATs from other existing platforms and databases, especially the vast reservoir of Thematic Networks platforms (i.e. Smart-AKIS, 4D4F).

The documentation on these digital tools will be collected – and summarised in fact sheets - through questionnaires which will cover the following issues:

- *Target audience:* for whom / which agricultural sector / which region was the tool developed?
- *Objectives:* what is the main goal of the tool? Which need does it address? What are the known challenges and benefits of using the DATS?
- *Technical information:* delivery mode, used data sources, required level of ICT knowledge, visual of the user interface.

Making the DATS available

The goal is to establish a multi-lingual digital tool for consultation by the community of advisers in the EU: **'**the digital adviser'. This web-based platform with a semantic search tool, will store digital farm advisory solutions and tools as its core domain. The semantic tool will assist advisers in identifying best-matching digital tools and alternatives to address specific, user-defined farmers' challenges expressed in 'common search language' built on components established in the VALERIE project (2017) and will tailor these to match the specific domains of the FAIRshare project.

Creating a learning network

A Permanent Networking Facility (PNF) will enable a live commentary on the inventory of digital tools in a user-friendly manner and become a collaboration tool between the advisors users and the providers. The key features for the management of this platform will be to (i) create new records, (ii) update existing records and finally (iii) search/query for results.

Results and discussion

The co-design process of the initial DATS collection interface is almost complete and ready for use. The project kick-off meeting in November 2018 included a participatory learning workshop aimed at ensuring that consortium members were comfortable working on specific tasks as teams. As is typical when using the multi-actor approach, the selection and classification framework started off with a huge number of possible variables and criteria. This was narrowed down by clustering and refinement into a structured format suitable for the collection of the information needed to inform the advisor user. For the collection of information, the potential DATS providers will be able to log in to their account and fill in a multi-page form. The form is designed in a user-friendly way and structured thematically for better navigation. The DATS provider will also be presented with suggested options and help tips, in order to make sure he/she completes the form in less time and with less effort. There are five main sections which have been formatted as outlined below.

- About the tool or service: gathering the following general overview information about DATS in an easy to use structures web page, with list and yes/no buttons used where possible. From the data entered here, it will be possible to catalogue the tools and provide full user information.
    - » Tool/service name
    - » Country of origin
    - » Language (s) (drop down list, multiple selection)
    - » Website /access point
    - » Cost – structure and type of cost
    - » Year of launch
    - » Year of last update
    - » Number of users - live
    - » Number of down loads
    - » Owner/creator (possible to insert multiple entries)
- Description: what it does and for who? This section gathers more detailed data on the user and application of the DATS, also the complexity and user training need.
    - » Who is the user? (list)

  - » Main target groups (multiple selection)
  - » Agricultural sector (list)
  - » Software type
  - » Use offline (Y/N)
  - » Source of data –(list, manual, downloadable)
  - » How it works (limit of words)
  - » Multi user access with permission (Y/N)
  - » Training required to use (Y/N)
- Challenges addressed by the DATS: This gathers information related to the challenge or problem to which the DATS may be applied in practice. This is to help the user find or identify a solution DAT to their need. Top five challenges addressed; next best five challenges addressed.
- Benefits of the tool**:** This enables the benefits of the DAT or service to be recorded and promoted and will support the new users of the 'Digital Advisor' platform in establishing the positive attributes as recorded by the DATS owner or existing user. Top five benefits; next best five benefits.
- Resources and support: This section records the look and feel of the DATS and provides useful support information and images including user testimonials.
  - » Keywords to describe tool
  - » Images and screenshots
  - » Uploaded manuals/sample reports
  - » Uploaded testimonials

Figure 1. Sample search result, informative single screen output from the 'Digital Advisor' platform

The user of the 'Digital Advisor' interface and permanent networking facility will be able to search the database with their own criteria. The goal is to populate the database with the collected information, in the most efficient way so as to return the most relevant results in the shortest time. Each result will correspond to a DATS record and its page will

be presented in one summary screen (Figure 1). The page of each DATS will be structured and presented in a way so that the user will be able:

- to make sure in a few seconds if the tool is right for them.
- to understand how it actually works, read testimonials, watch explanatory videos
- to decide if it meets their needs and resources (cost, technical skills, devices etc)
- to have direct access to the DATS (download it or test it)
- to contact the provider of the DATS.

The analysis of user feedback will inform the user interface through a continuous improvement process throughout the project. It is planned that at the end of the five year FAIRshare project, the platform will be hosted and maintained by the European Forum for Agricultural and Rural Advisors (EUFRAS) or other European associations.

References

Adrian, A.M., Norwood, S.H., & Mask, P.L. (2005). "Producers' perceptions and attitudes toward precision agriculture technologies", *Computers and Electronics in Agriculture,* 48(3): 256–271.

Chhachlar, A.R., and Hassan, S.H.J. (2013). The use of mobile phone among farmers for agricultural development. International Journal of Scientific Research, 2(6): 95–98.

EIP-Agri Focus group (2017). Benchmarking of farm productivity and sustainability performance. FINAL REPORT https://ec.europa.eu/eip/agriculture/sites/agri-eip/files/eip-agri_fg_benchmarking_final_report_2016_en.pdf.

Fountas, S., Blackmore, B., Ess, D., Hawkins, S., Blumhoff, G., Lowenberg-DeBoer, J. and Sørensen, C.G. (2005). Farmer Experience with Precision Agriculture in Denmark and the US Eastern Corn Belt. *Precision Agriculture*, 6(2): 121–141.

Fountas, S., Sorensen, C.G, Tsiropoulos, Z., Cavalaris, C., Liakos, V. and Gemtos, T. (2015). Farm machinery management information system. *Computers and Electronics in Agriculture*, 110: 131–138.

Gorman, M., Keogh, O., Clarke, P., Leonard, P. (2017). Using local radio and podcasts for agricultural extension in the west of Ireland. Paper presented to the 23rd European Seminar on Extension and Education, Chania, Greece.http://www.esee2017.gr/proceedings/proceedings.

Eurostat (2016). Farmers in the EU - statistics. https://ec.europa.eu/eurostat/statistics-explained/index.php/Farmers_in_the_EU_-_statistics#Socio-demographic_characteristics.

Grand View Research. (2017). https://www.grandviewresearch.com/press-release/global-precision-farming-market.

Jehan, N. Aukila, K.M., Shahzad, M., Jussain, A., Zahoor, M., Khan, M., and Bilal, A. (2014). Use of mobile phones by farming community and its impact on vegetable productivity. Pakistan *J. Agric. Res*., 27(1): 58–63.

JRC (2019). The contribution of precision agriculture technologies to farm productivity and the mitigation of greenhouse gas emissions in the EU EUR - Scientific and Technical Research Reports http://publications.jrc.ec.europa.eu/repository/handle/JRC112505

Krone, M., Schumacher, K.P., and Dannenberg, P. (2014). The impact of mobile phones on knowledge access and transfer of small-scale horticultural farmers in Tanzania. *Journal of the Geographical Society of Berlin*, 145(3): 158–161.

Kuta Yahaya, M. & Badiru, I. (2002). Measuring the Impact on Farmers of Agricultural Radio and Television Programs in Southwest Nigeria. *Journal of Applied Communications*, 86.

Marketsandmarkets (2015). CISION news feed https://www.prnewswire.com/news-releases/precision-farming-software--services-market-worth- 177-billion-by-2020–501205501.html

McBratney, A., Whelan, B., and Ancev, T. (2005). Future Directions of Precision Agriculture. *Precision Agriculture*, 6:7–23.

Nazari, M.R., and Hassan, S. (2011). The role of television in the enhancement of farmers' agricultural knowledge. *African Journal of Agricultural Research*, 6(4): 931–936.

Pierpaoli, E., Carli, G., Pignatti, E. and Canavari, M.(2013). Drivers of Precision Agriculture Technologies Adoption: A Literature Review. Procedia Technol. 8: 61–69.Poppe, K., & van Asseldonk, M. (2015). EIP-AGRI focus group benchmarking of farm productivity and sustainability performance: How can farmers and advisers use benchmarking data and process to improve productivity and sustainability performance? https://ec.europa.eu/eip/agriculture/sites/agri-eip/files/eip-agri_fg_benchmarking_final_report_2016_en.pdf

Poppe, K., Wolfert, S. and Renwick, A. (2015). A European Perspective on the Economics of Big Data. Farm Policy Journal, Edition: Vol. 12 No. 1, Chapter: 2, Publisher: Australian Farm Institute, Editors: Mick Keogh, pp.11–19.

SCAR AKIS (2017). SWG SCAR-AKIS Policy Brief on the Future of Advisory Services http://www.eufras.eu/images/Community/policy_brief_on_the_future_of_advisory_services_scar_akis_06102017.pdf

Valerie (2017). EU- FP7 project (www.valerie.euwww.ask-valerie.eu),

van Evert, F.K., Gaitán-Cremaschi, D., Fountas, S. and Kempenaar, C. (2017a). Can precision agriculture increase the profitability and sustainability of the production of potatoes and olives? *Sustainability*, 9(10).

van Evert, F.K., Fountas, S., Jakovetic, D., Crnojevic, V., Travlos, I. and Kempenaar, C. (2017b). Big Data for weed control and crop protection. *Weed Research* 57(4): 218–233.

Wolfert, S., Ge, L., Verdouw, C. and Bogaardt, JM. (2017). Big Data in Smart Farming – A review. *Agricultural Systems*, 153: 69–80.

Agriculture 4.0: Rapid, label-free nano-electrochemical based detection of bovine viral Diarrhoea virus (BVDV) and antibody (BVDAb) in serum

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Abstract

In farming and veterinary medicine, diagnostic tools enabling early detection of infectious disease in cattle could play a pivotal role in the control and eradication of bovine viral diarrhoea (BVD). Early identification of cattle persistently infected with virus (BVDV) through the availability of electronic test results to a veterinarian on-farm, would enable immediate diagnosis and isolation of an animal from a susceptible herd. A silicon chip-based biosensor platform, containing six gold nanoband electrodes as six individual sensors, was developed in this study to conduct detection of both bovine viral diarrhoea virus and antibody disease targets molecules. We demonstrate that the nanoband sensors have sufficient sensitivity and specificity for serological detection of both targets, and a low time-to-result (20 minutes). All examined serological samples were benchmarked against, and in complete agreement with, gold standard commercial ELISA data. These findings are of particular significance for potential on-farm point of use applications, where rapid analysis times and specificity are required to permit early diagnostics by veterinarians.

Keywords: real-time recognition, cough analysis, spectral analysis, signal processing

Introduction

Bovine viral diarrhoea is a disease that is endemic in many countries worldwide. The causative agent, bovine viral diarrhoea virus (BVDV), is a pestivirus. Viral infections result in reduced animal welfare, arising from immunosuppression, which has a significant economic cost for farmers through a combination of e.g. aborted foetuses and greatly reduced milk production (Peterhans and Schweizer, 2013; Graham *et al.*, 2015; Richter *et al.*, 2017). Its impact on animal health and the economics of livestock production has led to a number of European countries embarking on eradication schemes (Houe, 2003; Stott *et al.*, 2012). Currently, Norway, Sweden, Denmark, Switzerland, have achieved BVDV eradication (Bitsch *et al.*, 2000; Greiser-Wilke *et al.*, 2003; Nyberg *et al.*, 2004; Ståhl *et al.*, 2005; Presi *et al.*, 2011), whilst the Republic of Ireland is close to eradication following five years of a compulsory testing programme and removal of persistently infected (PI) animals. Persistent infections in cattle occur when a foetus is exposed to BVDV in utero and subsequently develop an immunotolerance to the virus (McClurkin *et al.*, 1984). These PI cattle shed virus throughout their lives (Houe, 1999), therefore in regions where BVDV is endemic, detection of virus and PI individuals is the method of choice to achieve eradication (Presi & Heim, 2010; Graham *et al.*, 2014). In countries where prevalence was lower, serological screening to detect exposure to BVDV is the preferred choice (Lindberg & Alenius, 1999; Rossmanith *et al.,* 2010; Norström *et al.*, 2014). For rapid progress to be made within an eradication programme, highly specific and sensitive assays are required. Moreover, the ability to be able to detect and identify both BVDV and antibodies expressed by an animal to this virus is essential (Lanyon *et al.,* 2014).

Currently, there are a number of methods for diagnosing both persistent and transient BVDV infections including: Several different types of enzyme linked immunosorbent assays (ELISA) (Howard *et al.,* 1985; Kramps *et al.*, 1999), polymerase chain reaction (PCR) assays (Belak & Ballagi-Pordany, 1991; Letellier & Kerkhofs, 2003) and virus isolation techniques (Saliki *et al.,* 1997; Cornish *et al.*, 2005). The majority of these assays are laboratory-based techniques. As such, they often require postal submission of samples to contract analysis labs with subsequent reporting of results to both veterinarian and farmers (Graham *et al.*, 2014). Both ELISA and PCR antigen detection techniques have been employed throughout the scheme with the aim of identifying virus positive and potentially PI cattle (Graham *et al.*, 2015). While the individual techniques are relatively quick to perform on receipt of samples to the laboratory (90–180 minutes), delivery of samples, laboratory logistics, and reporting of results, can delay PI detection, isolation and removal at farm level. The knock-on effect of this is further unnecessary viral spread within a herd.

A number of 'in-field' tests for detection of BVDV have been described including an immunochromatographic test (Kameyama *et al.*, 2006), rapid PCR test (Wakeley *et al.*, 2010) and ELISA-based method by IDEXX (SNAP, IDEXX Laboratories, Inc., Liebefeld, Switzerland). However, each of the tests are subject to constraints (i.e. long assay time, logistics of sample preparation and cost) which preclude their use from whole herd screening and incorporation into eradication schemes. More importantly, these tests focus on a single target, either BVD virus or antibody, (not both) meaning that two separate tests are required per animal adding additional cost to any disease eradication/surveillance scheme. An economical diagnostic device capable of rapid and sensitive detection of BVD (virus and antibody) in less than 30 minutes still remains elusive. In this regard, we aimed to investigate application of nano-electrochemical-based sensor technology to potentially deliver rapid and early identification of a disease state on-farm.

Electrochemical biosensors constitute a promising group of sensing devices suitable for remote viral detection (Pejcic *et al.*, 2006; Ciani *et al.*, 2012; Kiilerich-Pedersen *et al.*, 2013). In this paper, we present the development of a new silicon chip impedimetric immunosensor device based on nanoband electrodes and demonstrate co-detection of both BVDAb's and BVDV in bovine serum. The chip comprises six individually addressable gold nanoband sensors as well as gold counter and platinum pseudo reference electrodes. Sensor chips are also designed with a MicroSD style edge connector, to connect to external electronic circuitry, while also permitting simple swapping of the disposable chips necessary for in-field analysis. The highly miniaturised nature of these electrodes provide a number of advantages, when compared to larger micro and macro electrodes, including: steady-state behaviour (particularly beneficial for EIS); low charge transfer resistance; high current density due to enhanced mass transport; low depletion of target molecules; low supporting electrolyte concentrations; and faster response times (Arrigan, 2004; Dawson *et al.,* 2013). In this work, the performance of the immunosensors is assessed and characterised by challenging it with detection of virus and antibody target analytes in diluted serum and in whole serum. The sensor is challenged to discriminate between disease positive and disease negative serum samples from both TI and PI calves. BVD assay time-to-result is typically ~20 minutes demonstrating the potential of these nanoband electrochemical immunosensors for use in future on-farm diagnostic applications.

Material and methods

Materials and Reagents

BVDV-1 monoclonal antibody (RAE0823), specific to the envelop glycoprotein Erns was purchased from APHA Scientific, Weighbridge, UK. Recombinant Purified BVDV-1 Erns protein (BVDR16-R-10) was purchased from Alpha Diagnostic International. Serum

samples from BVDV PI's, BVDV negative, BVDAb seropositive and BVDAb seronegative animals were provided by Teagasc (Moorepark, Cork, Ireland). Acetate buffer (10 mM; pH 4) and ethanolamine-HCl (1mM) were obtained from Sierra Sensors GmbH (Germany). HBS-EP buffer was prepared by mixing 10mM HEPES, 150mM NaCl, 3mM EDTA and 0.005% Tween-20 in DI water and adjusted to pH to 7.4 with 5% sodium hydroxide solution. All other reagents were purchased from Sigma Aldrich unless otherwise stated and used as received. Deionized water (resistance 18.2 MΩ cm^{-1}) was obtained using an ELGA Pure Lab Ultra system.

Chip Design and Fabrication

Fabrication of the chips were similar to those described by Dawson (Dawson *et al.,* 2014). Gold nanoband electrodes were fabricated on four inch wafer silicon substrates bearing a ~300 nm layer of thermally grown silicon dioxide. Nanoband electrodes and wafer level optical alignment marks were first fabricated using a combination of optical lithography, metal evaporation (Ti 5 nm /Au 50 nm Temescal FC-2000 E-beam evaporator) and lift-off techniques to yield well-defined, stacked metallic (Ti/Au) nanoband (700 nm width, 50 nm height, 80 µm length) structures. Each chip consisted of six nanoband working electrodes (WE) spaced 800 µm apart. A second optical lithographic and metal deposition (Ti 10 nm/Au 100 nm) process, aligning to the as-deposited wafer level alignment marks, was then undertaken to define a MicroSD pinout, interconnection tracks as well as counter and reference electrodes (500 µm wide x 10 mm long), see Figure 1 (a) and (b). Finally, a third optical lithographic and metal deposition and lift-off process was undertaken, in a similar manner, to define the pseudo reference platinum (Ti/Pt 10/90 nm) reference electrode. In this work, an on-chip microSD style electrical pin-out was included to permit facile electrical connection to external electronics. In this manner, chips could be easily swapped in and out enabling rapid analysis of multiple samples. A custom built cell was designed and fabricated so that when screwed together, the microSD primary contact pads protruded out of the holder to allow connection with a PCB mounted microSD port, see Fig. 1 (c).

Electrical characterisation

Electrochemical experiments were carried out using an Autolab Potentiostat/ Galvanostat PGSTAT128N (Metrohm Ltd, Utrecht, The Netherlands) controlled by the Autolab NOVA software. Each sensor working electrode were characterised by Cyclic voltammetry (CV) and faradaic electrochemical impedance spectroscopy (EIS), in a 10 mM PBS solution (pH = 7.4) containing 1 mM FcCOOH. For CV, the potential was cycled from -200 mV to +600 mV versus the on-chip platinum pseudo reference electrode at a scan rate of 100 mV/s. The impedance measurements were performed over the frequency range from 100 mHz to 100 kHz at equilibrium potential of the FcCOOH (200 mV). The amplitude of the alternating voltage was 5 mV. All experiments were performed at room temperature in a Faraday cage.

Procurement of serum samples

Serum samples from BVDV PI's and uninfected animals have been acquired in Ireland since 2008. Samples were collected (under license from the Health Products Regulatory Authority, Ireland, project number AE19132/ P044) by jugular venipuncture in calves and coccygeal venipuncture in cattle over six months of age. All samples were archived at -80 °C and were subsequently made available to this study. Concerning viral analysis, BVDV infected individuals ranged in age from one week to four years, while BVDV negative individuals ranged from one week to nine years of age. Sera used in this study for virus detection, were first assayed in a commercial analytical lab using both AnDiaTec BoVir real time PCR kit (Kornwestheim, Germany) (2008 and 2009 samples) and the IDEXX BVDV PI

X2 Test (Maine, USA) (2010–2017 samples). Animals were classified as a PI if tested positive for BVDV on at least two occasions separated by an interval of at least three weeks.

Concerning antibody detection, BVDAb seropositive and seronegative samples were available from a Teagasc research project investigating the persistence of BVD antibodies in calves post-colostrum feeding. Sera used in this study for Ab detection were first assayed in a commercial analytical lab using IDEXX BVDV p80 Ab Test (Maine, USA) and results used to assign BVD serostatus to all samples.

Nanoband Electrode Biomodification

All chemical and bio modification steps were performed using the prefabricated chip holder and the PCB mounted microSD port to connect the chip to the external potentiostat. Cyclic voltammetry was then employed for electropolymerisation of o-aminobenzoic acid (o-ABA, 50 mM in 0.5 M H2SO4) to create a carboxylic terminated polymer layer at a gold electrode surface. An electrode was cycled eight times in the applied potential range of 0–0.8V at a scan rate of 50 mV/s. The first CV cycle displays an oxidative peak around 0.32 V corresponding to the formation of the polymer on the gold electrode subsequent scans, characteristic of the deposition of the o-ABA polymer on the gold surface. A fresh mixture of 1:1 EDC/NHS (75 mg/mL EDC and 11.5 mg/mL NHS) was then prepared in DI water and deposited onto a chip for 20 minutes to activate the carboxylic acid (COOH) surface. Working electrodes were coated with capture biomolecules and allowed incubate for one hour at 4 °C to allow covalent attachment to the electrode surface. Following this immobilization, electrodes were rinsed well with acetate buffer solution containing 0.1% Tween-20 (AB-T) and DI water and the un-reacted active sites were blocked by immersing in 1M ethanolamine HCl, pH 8.5 for 20 mins. Impedance measurement following this step were undertaken and considered as the "baseline" for on-chip sensors. To undertake analysis, as-modified electrodes were exposed to target solutions (BVDAb or BVDV) by 'spotting' 2 µL aliquots onto the electrode for 10 minutes incubation at room temperature. Electrodes were rinsed thoroughly with HBS-EP buffer and DI water to remove non-specifically bound target biomolecules prior to subsequent electrochemical measurement. Control experiments were undertaken, at appropriately bio-modified electrodes, using serum samples known to be negative, i.e. extracted from zero month healthy calves. In a similar manner, negative control samples were spotted (2 µL) serum test samples were spotted onto different electrodes on the same chip. All data were fitted using an equivalent circuit and experimental data were background subtracted using the values for the ethanolamine baseline as defined.

For antibody detection, electrodes were modified using with BVDV-1 Erns antigen as the capture biomolecule. A concentration of 100 µg/mL (acetate buffer, pH 4) was prepared, deposited and allowed incubate for one hour at 4 °C. BVDAb detection was then investigated in two samples: (i) BVD seropositive samples diluted with HBS-EP; in the range of 0.1–10% serum, and (ii) BVD seropositive and seronegative undiluted serum samples from one month old calves along with their corresponding pre-colostral negative sample (0 month). The spotting technique, described above, was employed to test negative control and positive sample on the same chip (n = 3). Further experiments were undertaken by pooling three seropositive (one month) samples and three seronegative (zero month) samples. All serum samples were incubated on an electrode for a total ~10 minutes.

For virus detection, electrodes were modified using BVD monoclonal antibody, specific to Erns antigen, as the capture biomolecule (100 µg/mL, acetate buffer, pH 4); incubated for one hour at 4 °C. The Erns structural protein is a model diagnostic antigen because Erns is readily secreted from infected cells during virus replication at an adequate

concentration for serological testing (Kuhne *et al.*, 2005; Aberle *et al.*, 2014). BVDV detection was investigated again using two solutions of increasing biological complexity. (i) BVDV positive and virus negative samples diluted with HBS-EP; in the range 0.1–10% serum, and (ii) BVDV positive (PIs) and virus negative control (0 month) undiluted sera samples. The spotting technique, described above, was again employed to test one negative and one positive sample per chip (n = 5). All serum samples were incubated on an electrode for a total ~10 minutes.

Results and discussion

Electrode Characterisation

An optical micrograph of a sensor chip is shown in Figure 1 (a). Each chip contained six separate nanoband working electrodes and gold counter and platinum pseudo-reference electrodes. A microSD pinout was implemented to allow facile and rapid interconnection with external instrumentation. Figure 1 (b) shows an optical micrograph of a single fully passivated single nanoband electrode (700 nm in width). The width of the passivation window opening (central dark rectangle) defined the exposed electrode length at 45 µm. Figure 1 (c) shows a sensor chip in a chip holder, prior to inserting the microSD pinout into a PCB mounted microSD connector. The well in the centre has a volume of ~100 µL, sealed onto the chip using an o-ring, and aligned over the on-chip sensor electrodes.

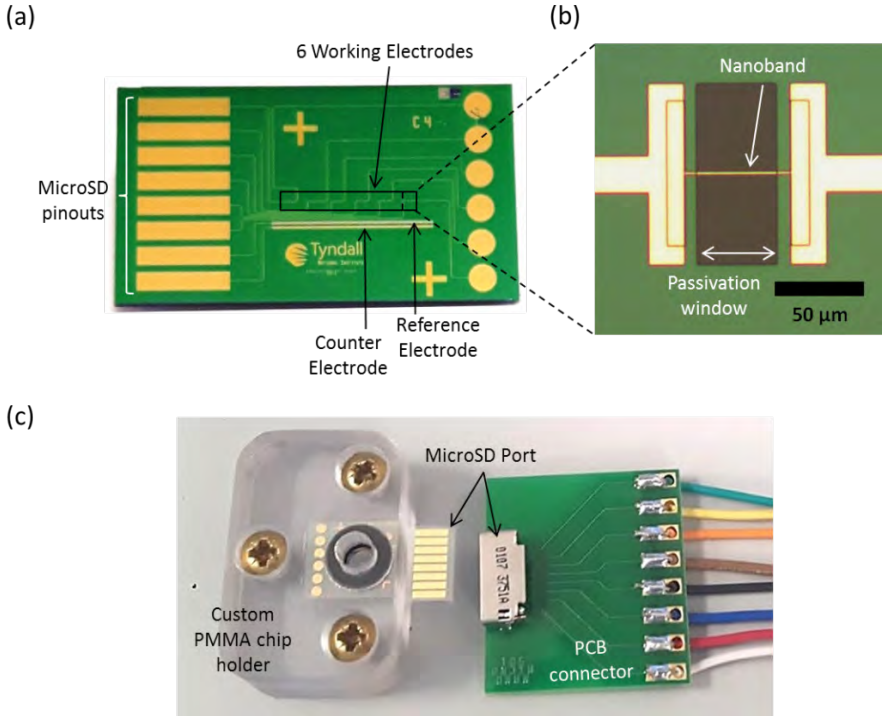

Figure 1. (a) Picture of fully integrated silicon sensor chip. (b) Optical micrograph of the single nanoband working electrode with dark passivation window. (c) Electrochemical setup with sensor chip and a PCB microSD connector

Electrodes were first characterised using cyclic voltammetry and electrochemical impedance spectroscopy, in presence of 1 mM FcCOOH redox probe. Figure 2 (a) shows a

typical CV voltammogram obtained using a pristine cleaned nanoband electrode exhibiting a quasi-steady-state behaviour, as expected (Dawson *et al.*, 2012; Wahl *et al.*, 2014). This steady-state behaviour is ideal for EIS and helps to correct for drift in the system. Faradaic impedance spectroscopy was performed on pristine gold electrodes and a typical Nyquist plot (real Z' vs imaginary Z" impedance), is presented in Figure 2 (b). The experimental data (blue dots) presented in Figure 2 (b) were fitted with an equivalent Randles circuit (Figure 2 (b) inset) modelled using the NOVA software. This fit data (solid line) overlays the experimental data (dots) extremely well, confirming the efficacy of the selected equivalent circuit components and defined values. When the nominal size of the working electrode is reduced, such as for the nano-size electrodes employed in this study, mass transport increases, and thus the current is no longer dominated by the diffusion of the redox ions toward the WE (Madou and Cubicciotti, 2003). As a result, the mass transfer dominated W becomes negligible and the Randles circuit can be simplified to a simple RC circuit.

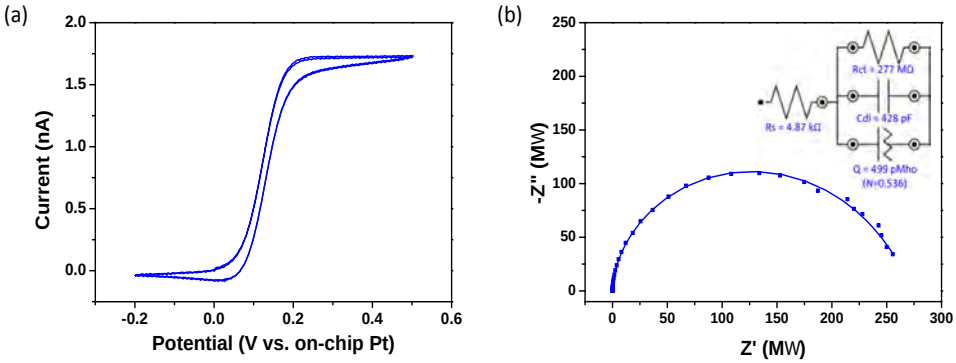

Figure 2. (a) ycliCc voltammogram of a gold nanoband electrode obtained in 1 mM FcCOOH in 10 mM PBS, pH 7.4, in the potential range of -0.2 V to 0.5 V at 100 mV/s. (versus on-chip platinum RE). (b) Nyquist plot for a clean gold electrode 0.1 mHz to 100 kHz

Detection of BVD in Diluted Serum

Both BVDAb and BVDV detections were first performed in diluted serum as a model immunoassay. The BVD Ab-virus complex can be considered as a coating film which provides a significant impedance response at the required sensitivity. A modified equivalent circuit, to account for the additional electrode bio-layers, was used to fit the results. Virus-modified sensors were applied to detection of BVDAb in diluted bovine sera of known disease state i.e. BVDAb seropositive and seronegative samples. Reverse experiments were also undertaken where antibody-modified sensors were employed for the detection of BVDV in virus positive and virus negative sera samples.

Antibody detection in Serum

Figure 3 (a) shows the nyquist diagrams, in presence of 1mM FcCOOH, of an electrode surface following modification and spotting of different dilutions of seropositive samples (0.1–10% serum). This dilution range was selected as it corresponds to the maximum dilution permitting the BVDAb detection with the ELISA (IDEXX) after 1 h incubation of the positive infected serum sample. The nyquist of 0.1% dilution (orange plot) does not reveal any measurable increase in the impedance ~140 MΩ versus the ethanolamine curve ~130 MΩ. Incubation with 0.5% serum sample leads to an increase in the impedance to ~200 Ω (red plot. Analysis of 0.2%, 0.3%, 1%, 5% and 10% sera shows an incremental increase in the impedance as the concentration of the antibody increased, exhibiting a semi-log relationship, see Figure 3(b). The observed changes in the nyquist spectra can be attributed to the binding of BVDAb to

the modified electrode. To explore the specificity of the modified sensors against BVDAb's and to assess the presence/degree of non-specific binding, control experiments were also undertaken using different electrodes on the same chips spotted with BVDAb seronegative samples. Following incubation, slight increases in the impedance, versus the ethanolamine curve were observed, arising from slight non-specific binding, see Figure 3 (b). Error bars represent six replicates. However, these data show that there is clear discrimination between BVD seropositive and seronegative bovine samples particularly at low dilution, i.e. 10% serum. This data strongly suggests that the sensors should be sufficiently sensitive and selective enough to discriminate between seropositive and seronegative in undiluted serum.

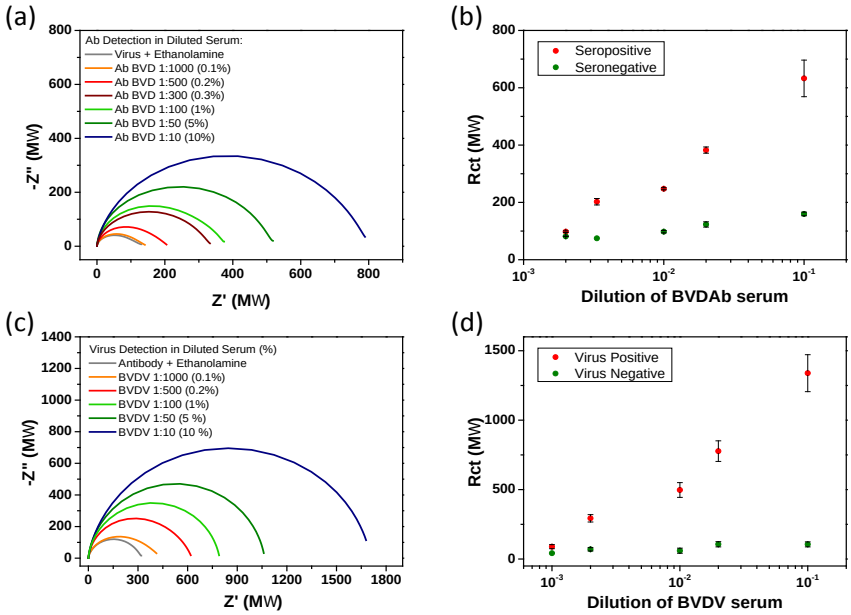

Figure 3. BVD antibody detection: (a) Nyquist plots obtained of virus modified gold nanoband electrode when exposed to different concentration of antibody (dilute sera samples). (b) Semi-log relationship of the charge transfer resistance versus virus concentration (n = six replicates). BVD virus detection: (c) Nyquist plots obtained of antibody modified gold nanoband electrode when exposed to different concentration of virus (dilute sera samples). (d) Semi-log relationship of the charge transfer resistance versus virus concentration (n = six replicates)

Virus Detection in Serum

In a similar manner, assays were undertaken to assess virus detection in diluted serum. Positive PI and virus negative control sera were spotted on different BVDAb modified sensors on a chip. Figure 3 (c) shows the impedimetric response for BVDV in 0.1 -10% diluted sera, measured for virus positive sera. All nyquist data were fit using the Randles-type circuit as described previously. An incremental increase in the impedance was observed, as the concentration of the virus is increased (decreasing dilution). The virus detection exhibits a larger impedance value (~600 – 1,700 MΩ, Fig. 3 (c)) compared to antibody detection (~200 – 800 MΩ, Figure 3 (a)), suggesting that binding of large BVDV to the modified electrode sterically hinders the electron transfer. Figure 3 (d) shows a semi-log relationship between virus concentration and measured signal. Error bars represent six replicates. This data verifies that the virus positive response arose from the binding of BVDV to the modified surface and demonstrates the potential for virus detection in undiluted serum.

Detection of BVD in Bovine Whole Serum Samples at MicroSD Devices

Antibody detection in Serum

A number of sensor chips were modified with virus (10 µg/mL) to test for BVDAb in pooled and unpooled seropositive and seronegative samples. Typical EIS measurements for the detection of BVDAb in a single calf (No. 8,954) obtained at time 0 month, and one month are presented in Figure 4 (a). Data from the seronegative sample produced an electrode impedance of ~350MΩ, a ~30 MΩ increase compared to the baseline attributed to small amounts of non-specific binding (green plot). A significant increase in impedance was observed, however, following incubation with a seropositive sample ~800 MΩ (red plot). This increase may be attributed to binding of the BVDAb's present in the serum to the viral modified electrode surface. Figure 4 (b) shows experimental background subtracted Rct EIS data in a bar chart format, obtained for a number of individual and pooled samples when undertaking BVDAb detection in seronegative and seropositive samples. Zero month samples (known to be seronegative) for an individual calf or pool are shown as dark green bars. These zero month samples all exhibited very low impedance (< 250 MΩ) for antibody detection, as expected. One month seronegative samples for two individual calves are presented as light green bars. The small difference in impedance values the zero and one month samples may be attributed to slight variation in the degree of non-specific adsorption and in electrode preparation. However, a clear increase in the electron-transfer resistance (> 800 MΩ) red bars is observed between the negative controls and both individual and pooled seropositive samples, (time to results 20 minutes).

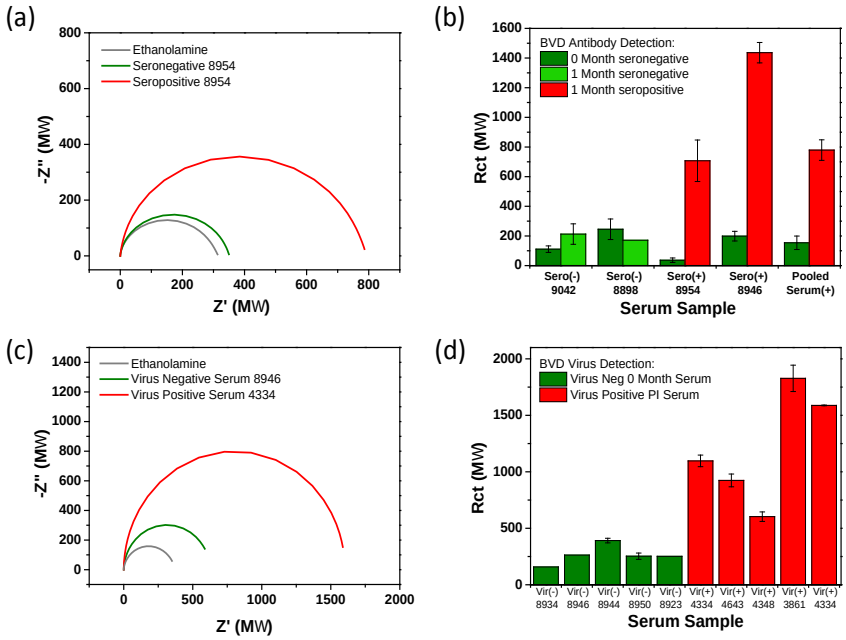

Figure 4. (a) Nyquist plots of seropositive and seronegative blood deposition on BVDV (10 µg/mL) modified microelectrodes, in the presence of 10 mM PBS containing 1 mM FcCOOH. (b) Bar chart comparison of seropositive and seronegative samples and their respective control samples. (c) Nyquist plots of a virus negative and virus positive PI serum, deposited on a BVDAb modified chip (measured in the presence of 1 mM FcCOOH). (d) Bar chart showing PI serum and virus negative serum samples.

Virus in Serum

Sensor chips, modified with monoclonal BVDAb (10 µg/mL), were then employed to test for the presence of BVDV in PI calf whole serum. Nyquist plots, illustrating detection of BVDV positive serum (from PI calf 4,334) and BVDV negative serum (from 0 month calf 8,946) are shown in Figure 4 (c). The deposition of BVDV negative serum 8,946 shows an Rct of ~600 MΩ, which increased slightly following the ethanolamine baseline, Figure 4 (c) green plot. On a separate electrode on the same chip, the target virus positive PI serum was immobilised and an increased Rct value was measured ~1,600 MΩ. In total, five BVDV negative samples (green) and five BVDV positive PI samples (red) were examined and the Rct value measured, Figure 4 (d) (time to results 20 minutes). The chart in Figure 4 (d) shows the background subtracted Rct data for these assays. As expected the virus negative sera exhibited minor NSB binding to the electrode (<400 MΩ), whereas the target seropositive one month samples present a significant increase in the electron-transfer resistance (> 800 MΩ). These results demonstrate there is successful serological binding of the BVDAb to the immobilised viral protein. The results presented above clearly demonstrate that the nanoband sensors have sufficient sensitivity and specificity for detection of both target antibody and virus detection in serum. The findings are of particular significance for on-farm point of care applications where high sensitivity and specificity and low time-to-result, are required to permit early diagnostics by veterinarians.

Benchmarking against ELISA

ELISA tests were performed using a commercial BVDV p80 Ab detection kit for the detection of specific antibodies directed to bovine viral diarrhoea virus (IDEXX, UK). Briefly, the p80 modified ELISA plate of the kit was exposed to the serum samples diluted (10%) in the commercial dilution solution. The conjugate was diluted (with the provided solution) and incubated in the plate for 30 minutes at room temperature. After washing, a chromogenic substrate was added for 20 minutes in dark room at room temperature. Finally, the reaction revealing the conjugate was stopped using the commercial stop solution and the absorbance value was read at 450 nm using an ELISA plate reader (DIASource, Belgium). All of the impedimetric results were compared with and were fully in agreement with their respective The findings are of particular significance for on-Farm point of use applications where high sensitivity and specificity and low time-to-results, are required to permit early diagnostics by veterinarians.

Conclusions

We present new sensor chips that comprise six on-chip nanoband electrodes, integrated counter and pseudo reference electrode and a micro SD style pin-out connection to facilitate facile connection to external circuitry. Biomolecules were immobilised at nanoband electrodes using an electrodeposited polymer anchor layer followed by EDC based covalent coupling of capture probe material to provide a bio-modification process that could withstand cleaning protocols without degradation. Appropriately modified sensors were challenged with their target analytes in two different media with increased levels of biological complexity. In both cases, the sensors exhibited excellent specificity easily distinguishing between positive and negative samples while also exhibiting a semi-log linear dependency between concentration and increase in charge transfer resistance. Concerning whole serum, the sensors were benchmarked and in all cases were in agreement with commercial ELISA laboratory results. These proof-of-concept studies in sera samples are very promising in that they show clear differentiation between BVD (antibody and virus) positive and negative sera samples. The nanoband sensors demonstrate the capability to detect both virus and antibodies in whole serum, which is an essential prerequisite for on-farm BVD serological screening and surveillance. The short measurement times ~20 minutes also satisfies the time requirements for on-farm analysis.

Acknowledgements

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References

Aberle, D., Muhle-Goll, C., Bürck, J., Wolf, M., Reißer, S., Luy, B., Wenzel, W., Ulrich, A.S., Meyers, G. (2014). Structure of the Membrane Anchor of Pestivirus Glycoprotein E(rns), a Long Tilted Amphipathic Helix. PLoS Pathogens 10, e1003973.

Arrigan, D.W.M. (2004). Nanoelectrodes, nanoelectrode arrays and their applications. *The Analyst* 129, 1157–1165.

Belak, S., Ballagi-Pordany, A. (1991). Bovine viral diarrhea virus infection: rapid diagnosis by the polymerase chain reaction. Ruminant Pestivirus Infections. Springer, 181–190.

Bitsch, V., Hansen, K.E.L., Rønsholt, L. (2000). Experiences from the Danish programme for eradication of bovine virus diarrhoea (BVD) 1994-1998 with special reference to legislation and causes of infection. *Veterinary Microbiology,* 77.

Ciani, I., Schulze, H., Corrigan, D.K., Henihan, G., Giraud, G., Terry, J.G., Walton, A.J., Pethig, R., Ghazal, P., Crain, J., Campbell, C.J., Bachmann, T.T., Mount, A.R. (2012). Development of immunosensors for direct detection of three wound infection biomarkers at point of care using electrochemical impedance spectroscopy. *Biosensors and Bioelectronics*, 31: 413–418.

Cornish, T.E., Olphen, A.L.v., Cavender, J.L., Edwards, J.M., Jaeger, P.T., Vieyra, L.L., Woodard, L.F., Miller, D.R., O'Toole, D. (2005). Comparison of Ear Notch Immunohistochemistry, Ear Notch Antigen-Capture ELISA, and Buffy Coat Virus Isolation for Detection of Calves Persistently Infected with Bovine Viral Diarrhea Virus. *Journal of Veterinary Diagnostic Investigation*, 17: 110–117.

Dawson, K., Baudequin, M., Sassiat, N., Quinn, A.J., O'Riordan, A. (2013a). Electroanalysis at discrete arrays of gold nanowire electrodes. *Electrochimica Acta,* 101: 169–176.

Dawson, K., Baudequin, M., Sassiat, N., Quinn, A.J., O'Riordan, A. (2014). Electroanalysis at ultramicroand nanoscale electrodes: a comparative study. *Journal of the Electrochemical Society*, 161: B3055-B3060.

Dawson, K., Wahl, A., Murphy, R., O'Riordan, A. (2012). Electroanalysis at Single Gold Nanowire Electrodes. *J Phys Chem*, C 116: 14665–14673.

Graham, D.A., Clegg, T.A., O'Sullivan, P., More, S.J. (2015). Survival time of calves with positive BVD virus results born during the voluntary phase of the Irish eradication programme. *Preventive Veterinary Medicine*, 119: 123–133.

Graham, D.A., Lynch, M., Coughlan, S., Doherty, M.L., Neill, R., Sammin, D., Flaherty, J. (2014). Development and review of the voluntary phase of a national BVD eradication programme in Ireland. *Veterinary Record*, 174: 67.

Greiser-Wilke, I., Grummer, B., Moennig, V. (2003). Bovine viral diarrhoea eradication and control programmes in Europe. *Biologicals* 31.

Houe, H. (1999). Epidemiological features and economical importance of bovine virus diarrhoea virus (BVDV) infections. *Veterinary Microbiology,* 64: 89–107.

Houe, H. (2003). Economic impact of BVDV infection in dairies. Biologicals, 31: 137–143.

Howard, C.J., Clarke, M.C., Brownlie, J. (1985). An Enzyme-Linked Immunosorbent Assay (ELISA) for the detection of antibodies to Bovine Viral Diarrhoea Virus (BVDV) in cattle sera. *Veterinary Microbiology,* 10, 359–369.

Kameyama, K., Sakoda, Y., Tamai, K., Igarashi, H., Tajima, M., Mochizuki, T., Namba, Y., Kida, H. (2006). Development of an immunochromatographic test kit for rapid detection of bovine viral diarrhea virus antigen. Journal of Virological Methods, 138: 140–146.

Kiilerich-Pedersen, K., Daprà, J., Cherré, S., Rozlosnik, N. (2013). High sensitivity point-of-care device for direct virus diagnostics. *Biosensors and Bioelectronics,* 49: 374–379.

Kramps, J.A., Maanen, C.v., Wetering, G.v.d., Stienstra, G., Quak, S., Brinkhof, J., Rønsholt, L., Nylin, B. (1999). A simple, rapid and reliable enzyme-linked immunosorbent assay for the detection of bovine virus diarrhoea virus (BVDV) specific antibodies in cattle serum, plasma and bulk milk. *Veterinary Microbiology,* 64: 135–144.

Kuhne, S., Schroeder, C., Holmquist, G., Wolf, G., Horner, S., Brem, G., Ballagi, A. (2005). Detection of bovine viral diarrhoea virus infected cattle–testing tissue samples derived from ear tagging using an Erns capture ELISA. Zoonoses and Public Health 52, 272–277.

Lanyon, S.R., Hill, F.I., Reichel, M.P., Brownlie, J. (2014). Bovine viral diarrhoea: Pathogenesis and diagnosis. *The Veterinary Journal*, 199: 201–209.

Letellier, C., Kerkhofs, P. (2003). Real-time PCR for simultaneous detection and genotyping of bovine viral diarrhea virus. *Journal of Virological Methods,* 114: 21–27.

Lindberg, A.L.E., Alenius, S. (1999). Principles for eradication of bovine viral diarrhoea virus (BVDV) infections in cattle populations. *Veterinary Microbiology,* 64: 197–222.

Madou, M.J., Cubicciotti, R. (2003). Scaling issues in chemical and biological sensors. Proc. IEEE 91, 830–838.

McClurkin, A.W., Littledike, E.T., Cutlip, R.C., Frank, G.H., Coria, M.F., Bolin, S.R. (1984). Production of cattle immunotolerant to bovine viral diarrhea virus. *Can J Comp Med,* 48: 156–161.

Norström, M., Jonsson, M.E., Åkerstedt, J., Whist, A.C., Kristoffersen, A.B., Sviland, S., Hopp, P., Wahlström, H. (2014). Estimation of the probability of freedom from Bovine virus diarrhoea virus in Norway using scenario tree modelling. *Preventive Veterinary Medicine,* 116: 37–46.

Nyberg, O., Østeras, O., Plym Forshell, K. (2004). Eradication of BVDV-infection in Norwegian cattle 1992-2003 - A success story. Proceedings of the Second European Symposium on BVDV control. Oporto, Portugal.

Pejcic, B., Marco, R.D., Parkinson, G. (2006). The role of biosensors in the detection of emerging infectious diseases. *The Analyst* 131, 1079–1090.

Peterhans, E., Schweizer, M. (2013). BVDV: A pestivirus inducing tolerance of the innate immune response. *Biologicals*, 41: 39–51.

Presi, P., Heim, D. (2010). BVD eradication in Switzerland—A new approach. *Veterinary Microbiology*, 142: 137–142.

Presi, P., Struchen, R., Knight-Jones, T., Scholl, S., Heim, D. (2011). Bovine viral diarrhea (BVD) eradication in Switzerland--Experiences of the first two years. *Preventive Veterinary Medicine,* 99.

Richter, V., Lebl, K., Baumgartner, W., Obritzhauser, W., Käsbohrer, A., Pinior, B. (2017). A systematic worldwide review of the direct monetary losses in cattle due to bovine viral diarrhoea virus infection. *The Veterinary Journal*, 220: 80–87.

Rossmanith, W., Deinhofer, M., Janacek, R., Trampler, R., Wilhelm, E. (2010). Voluntary and compulsory eradication of bovine viral diarrhoea virus in Lower Austria. *Veterinary Microbiology*, 142: 143–149.

Saliki, J.T., Fulton, R.W., Hull, S.R., Dubovi, E.J. (1997). Microtiter virus isolation and enzyme immunoassays for detection of bovine viral diarrhea virus in cattle serum. *Journal of Clinical Microbiology,* 35: 803–807.

Ståhl, K., Kampa, J., Baule, C., Isaksson, M., Moreno-López, J., Belák, S., Alenius, S., Lindberg, A. (2005). Molecular epidemiology of bovine viral diarrhoea during the final phase of the Swedish BVD-eradication programme. *Preventive Veterinary Medicine*, 72: 103–108.

Stott, A.W., Humphry, R.W., Gunn, G.J., Higgins, I., Hennessy, T., O'Flaherty, J., Graham, D.A. (2012). Predicted costs and benefits of eradicating BVDV from Ireland. *Irish Veterinary Journal*, 65: 12.

Wahl, A., Barry, S., Dawson, K., MacHale, J., Quinn, A.J., O'Riordan, A. (2014). Electroanalysis at Ultramicro and Nanoscale Electrodes: A Comparative Study. *Journal of the Electrochemical Society* 161: B3055-B3060.

Wakeley, P.R., Errington, J., Squirrell, D. (2010). Use of a field-enabled nucleic acid extraction and PCR instrument to detect BVDV. *Veterinary Record,* 166: 238.

Evaluation of an audio-based sensor platform to classify patterns of clinical respiratory episodes in large growing pig populations

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Abstract

Audio-based sensor systems hold the potential to remotely differentiate the primary etiology of clinical episodes of respiratory disease. The purpose of this project was to evaluate the ability of an audio-based sensor system to classify patterns of clinical respiratory disease in growing pigs according to their primary etiology under large-scale commercial production conditions.

Audio sensor devices were installed in three large commercial wean-to-finish facilities designed to house 1,200–2,400 pigs per airspace. An algorithm-based respiratory distress index (RDI) was continuously generated from recorded sound files and uploaded to a cloud database. The data were charted and patterns of cough were categorised. For each RDI episode, diagnostic samples were collected and tested by PCR for PRRS, IAV-S, Mycoplasma hyopneumoniae, PCV2 and parainfluenza. Episodes were aligned with their corresponding diagnostic results and the resulting aggregate cough patterns were characterised. Two RDI patterns were detected across the three farm sites, one associated with IAV-S (H1N1 or H3N2), and another associated with Mycoplasma hyopneumoniae. IAV-S associated RDI patterns had a distinctive bi-modal shape, whereas the pattern associated with Mycoplasma hyopneumoniae showed a gradual relatively linear rising pattern. The ability to classify cough patterns by primary etiology is useful at both a local site and global aggregate levels. With this information, local site managers can better adjust and respond with more timely, appropriate diagnostics and treatment. Further, those responsible for flows/systems and areas/networks can better assess larger scale behaviour of specific disease agents and the clinical impact of intervention and control protocols.

Keywords: cough patterns, respiratory distress

Introduction

Producers and veterinarians routinely rely on both observation and data to make clinical assessments of farms and animals, as well as conduct diagnostic investigations to uncover causes and contributing factors of what they judge to be economically and welfare relevant clinical health issues. During the workday and farm walk-through visits, farm personnel and veterinarians use various visual and audio cues to assess the animals and their environment and interpret the cues. Also, recorded daily farm data and production records are reviewed and interpreted to augment observations.

Skills in assessment and interpretation of visual and audio cues, as well as of recorded farm data typically improve with experience. However, these activities can be time-consuming, and are problematic where availability of enough skilled and experienced labour is often a major constraint. Further, the period of animal observation is constrained to typical workday hours, leaving substantial time each day that animals are not observed during at least two-thirds of each weekday as well as by reduced numbers of staff during weekends and holidays. These dynamics can serve to delay detection of clinical health

and performance issues, and, in turn, delay interventions – risking welfare, productivity and profitability.

Important audio cues come in the form of sounds like coughing and sneezing of pigs. Sound in the form of cough has been researched for use as a semi-manual clinical assessment and quasi-diagnostic tool (Bahnson *et al.,* 1994; Morris *et al.,* 1995; Nathues *et al.,* 2012). Further, the routine quantification of cough via use of smart devices and an app under commercial conditions has been evaluated for more objective clinical assessment and to better direct diagnostic investigation (Schagemann *et al.,* 2016). While useful, the manual collection of cough data can be problematic under commercial operational conditions. Even when aided by current technologies such as smart phones or tablets and an app, the manual collection of cough data along with management, analysis and interpretation can be time-consuming and require adherence to an execution protocol. Also, while applying a systematic process and related algorithm is more objective than a traditional herd walk-through, a degree of subjectivity still remains where farm production personnel and/or veterinarians are counting coughs.

The need for, value of and various forms of automated and objective assessment and quantification of pig health and welfare have been described, including various categories of technologies useful for these purposes (Matthews *et al.,* 2016). These sensor and device technologies, utilised within the framework of a coordinated real-time system, can collectively be called "Precision Livestock Farming". Precision Livestock Farming (PLF) has been defined as: "*…to manage individual animals by continuous real-time monitoring of health, welfare, production/reproduction, and environmental impact*." (Berckmans, 2017). As a deliverable for the four year EU-PLF project, a "blueprint" for implementation of PLF has been outlined and developed, including descriptions of some PLF technologies (Guarino *et al.,* 2017). Various PLF-oriented technologies have been researched, including sound (VanHirtum & Berckmans, 2002; Guarino *et al.,* 2008). Further, in recent years commercial sound-oriented PLF technologies have begun to be evaluated in commercial settings (Finger *et al.,* 2014; Genzow *et al.*, 2014a; Genzow *et al.,* 2014b; Hemeryck *et al.*, 2015; Polson *et al.,* 2018).

The early detection of clinical respiratory disease in growing pigs can contribute to improved productivity and profitability through enabling earlier more effective treatment. While clinical disease detection is the direct responsibility of farm personnel detection of clinical disease onset across multiple farms and systems can be problematic due to variation in their skill, experience and time spent in the farm. Continuous sound monitoring systems can complement and enhance farm personnel and veterinary observation for detection of clinical episodes of respiratory disease. Such systems have been shown to detect the onset of clinical respiratory disease earlier than farm personnel, and hold the potential to do so earlier with greater consistency, reliability, objectivity and precision (Berckmans *et al.,* 2015).

To assess the utility of sound as a "sample" type in swine for the detection and characterisation of clinical respiratory disease, an audio device, sensors and software platform designed to monitor respiratory distress in pigs were evaluated (SOMO+, SoundTalks NV, Leuven, Belgium). The objectives of this evaluation were to:

- Assess the ability of the SOMO+ system to reliably detect the onset and directionality of clinical respiratory disease of growing pigs under large-scale commercial production conditions
- Assess the ability of the SOMO+ system to classify patterns of clinical respiratory disease in growing pigs according to their primary etiology under large-scale commercial production conditions

Materials and methods

Three different farm sites / systems were enrolled in the project. Pigs were placed into facilities per normal practice. Cough monitors (SOMO+ Respiratory Distress Monitor, SoundTalks NV, Leuven, Belgium) were obtained and installed in three large commercial wean-to-finish facilities designed to house 1,200–2,400 pigs per airspace (Figure 1). Five devices were installed in each of the two 1,200 head buildings, spaced equidistant from each other along the center alleyway. In the 2,400 head building, 11 devices were installed, with four devices over the middle of the pens on each side of the building spaced equidistant from each other and three in the central alleyway spaced equidistant from each other.

Once installed, the SOMO+ devices continuously monitored temperature using two sensors and humidity using one sensor. Also, each device had one connected microphone continuously recording sound. An algorithm was applied to the continuous stream of sound and classified specific sound events as coughs. The sound events classified as coughs were then counted, with the counts uploaded to a cloud database with a web user interface. A mobile app was used to monitor the SOMO+ devices remotely from a smart device (e.g. smart phone or tablet). An algorithm-based respiratory distress index (RDI) was continuously generated from the recorded sound files and cough counts, and was accessible via the web and app interfaces for monitoring and evaluation of various dynamic visualization tools, including summary tables and charts.

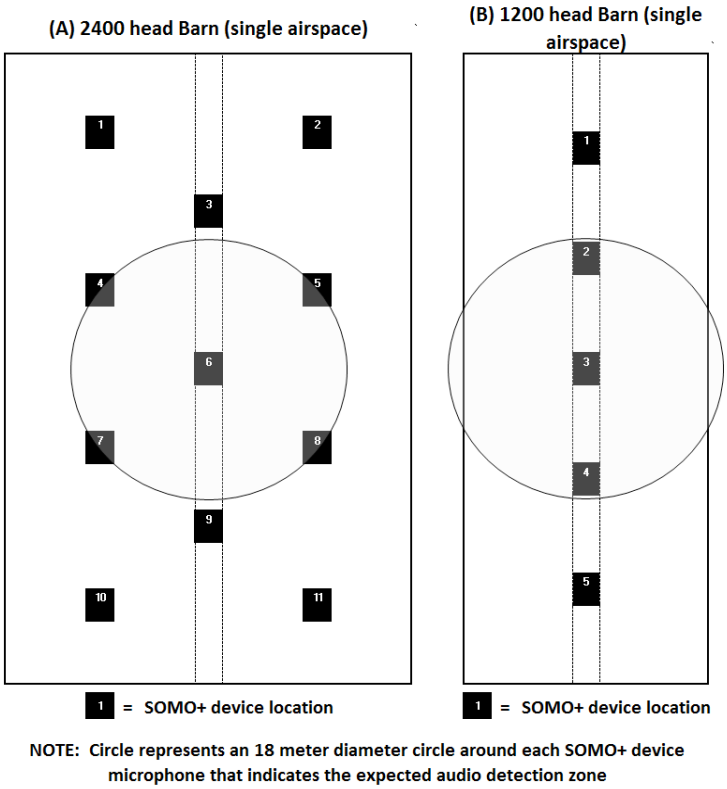

Figure 1. Placement of SOMO+ devices to determine optimal detection zone size, number and configuration to maximise cough detection and directionality determination

RDI's were continuously monitored and alerts were automatically sent to pre-determined personnel when a significant rise in RDI was detected by the system's algorithm. When an RDI alert was generated, diagnostic samples were collected via cotton rope-origin oral fluid sampling and/or laryngeal swab sampling and tested by PCR for PRRS, IAV-S, Mycoplasma hyopneumoniae, PCV2 and parainfluenza. RDI episodes were aligned with their corresponding diagnostic results using event creation and tracking tools available via the web site interface. The resulting aggregate cough patterns were then characterised according to the diagnostic results. Other personnel observations representing "notable events" were recorded for each barn airspace and site using tools available via the web site interface.

Results and discussion

RDI episodes were detected across the three farm sites, including: IAV-S (H1N1), IAV-S (H3N2), and Mycoplasma hyopneumoniae (Figure 2). Diagnostic testing of oral fluid samples and laryngeal swabs by PCR and sequencing confirmed the presence of IAV-S (H1N1), IAV-S (H3N2) and Mycoplasma hyopneumoniae for the three RDI episodes, respectively. PRRS PCR testing results were negative for all samples collected at all three RDI episodes.

Two distinctive RDI patterns were detected across the three farm sites, one associated with IAV-S (H1N1 or H3N2), and another associated with Mycoplasma hyopneumoniae. IAV-S associated RDI patterns had a distinctive bi-modal shape, whereas the pattern associated with Mycoplasma hyopneumoniae showed a gradual relatively linear rising pattern. These observations were generally consistent with those described in prior work using the SoundTalks technology (Genzow *et al.*, 2014a; Genzow *et al.*, 2014b). The detection of the respiratory disease episodes by the SOMO+ Respiratory Disease Monitor ranged from an estimated 2-5 days earlier than detection by farm personnel, consistent with the observations of Berckmans *et al.* (2015).

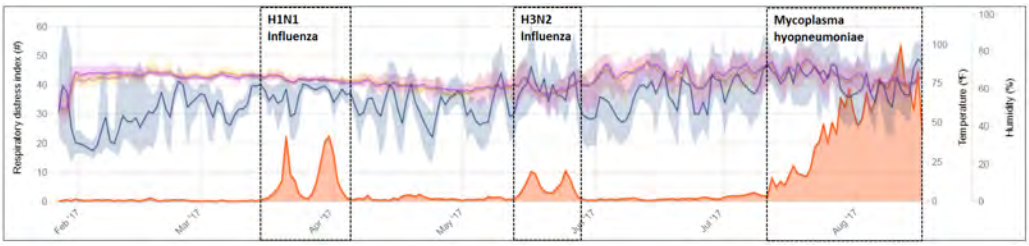

Figure 2. Example of a Respiratory Disease Index (RDI) chart with temperature and humidity data from a 2,400 head wean-to-finish barn experiencing clinical episodes of Influenza and Mycoplasma

The ability to use a combination of RDI data and diagnostic testing results to classify cough patterns according to primary etiology is useful at both a local site and global aggregate levels. With this information, farm personnel and area/flow field managers can, over time, learn to better adjust and respond with more timely, appropriate diagnostics and treatment. Further, those responsible for overall business entity flow-level operations, as well as inter-business areas/networks can better assess larger scale behaviour over time of specific disease agents and the clinical impact of intervention and control protocols.

The ability of the multiple device configuration to determine directionality of RDI episodes was assessed. The directionality of the onset and progression of the IAV-S (H1N1) and Mycoplasma hyopneumoniae episodes throughout the 2,400 head barn were evident in the data (Figure 3).

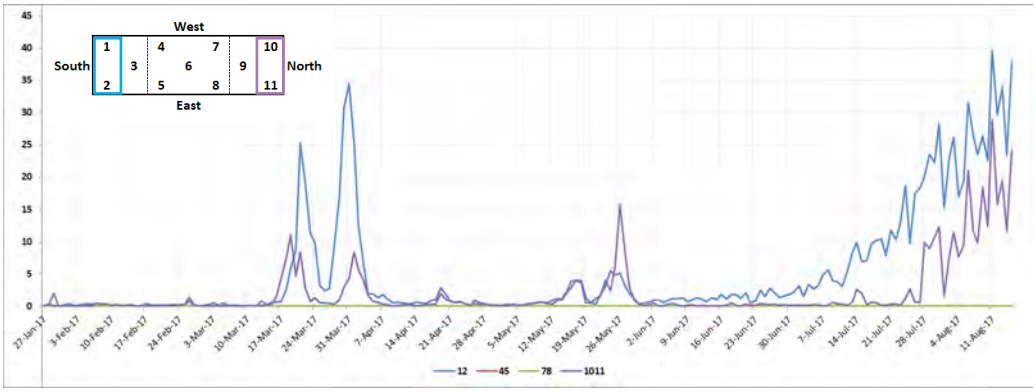

Figure 3. Example of the ability of a configuration of multiple SOMO+ devices to determine spatial directionality of the onset of cough episodes

Each device represents an 18-20 meter diameter sound detection "zone". Within the footprint of an airspace, the detection and directionality of cough is then a function of the square meters covered by the "zones" out of the total possible square meters in that contiguous airspace. As such, the detection, directionally and movement (ebb and flow) of RDI episodes through the airspace are made possible, enabling better characterisation and understanding of respiratory disease behaviour.

Conclusions

Monitoring the health and performance of growing pigs by using audio-based devices and sensors to capture, quantify, assess directionality of and categorise sound events such as coughing can enable earlier and more precise detection of relevant clinical episodes, and result in more timely and targeted intervention. In doing so, the impact of respiratory disease on animal welfare and performance can be better minimised and the related financial impact can be better reduced, enabling optimisation of profitability.

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References

Bahnson, P., Marsh, W., Dial, G. (1994). The associations among serology to M. hyopneumoniae, lesions at slaughter, and a clinical index of cough in groups of growing pigs. In: Poomvises P. and Ingkaninun P. (eds) *Proceedings*. The 13th International Pig Veterinary Society Congress, Tiranasah Press, Bangkok, Thailand, pp. 131.

Berckmans, D. (2017). General introduction to precision livestock farming. *Animal Frontiers*, 7(1): 6–11.

Berckmans, D., Hemeryck, M., Berckmans, D. (2015). Animal Sound…Talks! Real-time Sound Analysis for Health Monitoring in Livestock. In: Ni J-Q., Lim Te-T. and Wang C. (eds) *Proceedings*. The International Symposium on Animal Environment and Welfare, China Agriculture Press, Beijing, China, pp. 215–222.

Finger, G., Hemeryck, M., Duran, C.O., Genzow, M. (2014). Practical application of the Pig Cough Monitor in a German fattening pig herd with PRDC. In: Hernandez J. and Zimmerman J. (eds) *Proceedings*. The 23rd International Pig Veterinary Society Congress, [IPVS23], Cancun, Mexico, pp. 207.

Genzow, M., Duran, C.O., Strutzberg-Minder, K., Finger, G., Hemeryk, M. (2014a). Monitoring of a commercial fattening herd by means of the Pig Cough Monitor and oral fluid diagnostics. In: Hernandez J. and Zimmerman J. (eds) *Proceedings*. The 23rd International Pig Veterinary Society Congress, [IPVS23], Cancun, Mexico, pp. 205.

Genzow, M., Duran, C.O., Hemeryck, M., Finger, G. (2014b) Course of cough in two batches of fattening pigs with different respiratory pathogen exposure. In: Hernandez J. and Zimmerman J. (eds) *Proceedings.* The 23rd International Pig Veterinary Society Congress, [IPVS23], Cancun, Mexico, pp. 212.

Guarino, M., Jans, P., Costa, A., Aerts J-M., Berckmans, D. (2008). Field testing of algorithm for automatic cough detection in pig houses. *Computers and Electronics in Agriculture,* 62: 22–28.

Guarino, M., Norton, T., Berckmans, D., Vranken, E., Berckmans, D. (2017). A blueprint for developing and applying precision livestock farming tools: A key output of the EU-PLF project. *Animal Frontiers,* 7(1): 13–17.

Hemeryck, M., Berckmans, D., Vranken, E., Tullo, E., Fontana, I., Guarino, M., van Waterschoot, T. (2015). The Pig Cough Monitor in the EU-PLF project: results and multimodal data analysis in two case studies. In: Guarino M. (ed) *Proceedings.* The 7th European Conference on Precision Livestock Farming, University of Milan, Milan, Italy, pp. 147–155.

Matthews, S., Miller, A., Clapp, J., Plotz, T., Kyriazakis, I. (2016). Early detection of health and welfare compromises through automated detection of behavioural changes in pigs. *The Veterinary Journal,* 217: 43–51.

Morris, C., Gardner, I., Hietala, S., Carpenter, T. (1995). Enzootic Pneumonia: Comparison of Cough and Lung Lesions as Predictors of Weight Gain in Swine. *Canadian Journal of Veterinary Research,* 59(3): 197–204.

Nathues, H., Spergser, J., Rosengarten, R., Kreienbrock, L., Grosse Beilage, E. (2012). Value of the clinical examination in diagnosing enzootic pneumonia in fattening pigs. *The Veterinary Journal,* 193(2): 443–447.

Polson, D., Playter, S., Berckmans, D., Stoffel, A., Quinn, B., Genzow, M., Duran, C.O. (2018). Precision Livestock Farming (PLF) for pig health and production: Sound as a diagnostic sample. In: Culhane M. and Polson D. (eds) *Preconference: The 4-dimensional revolution in food animal health and production.* The 49th Annual Meeting of the American Association of Swine Veterinarians; San Diego, California USA, [AASV], pp. 21–24.

Schagemann, G., Wertenbroek, N., Langhoff, R., De Jonghe, E., Eppik, L., Figueras, S., Mesu, P. (2016). Cough Control Program for the identification of respiratory pathogens in PRDC farms. In: Martelli P. and Nathues H. (eds) *Proceedings*. The 24th International Pig Veterinary Society Congress, Royal Dublin Society, Dublin, Ireland, pp. 342.

Van Hirtum, A. and Berckmans, D. (2002). Automated recognition of spontaneous versus voluntary cough. *Medical Engineering and Physics*, 24: 541–545.

First results of a practical validation of signal feeding - an automated operant conditioning in sows

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Abstract

Signal feeding – an automated operant conditioning for acoustic signals that indicate the individual availability of feed – has been shown to be an effective cognitive environmental enrichment for group housed pigs. Moreover, it reduced queuing behaviour and the number of severe lesions in a dynamic large group in a previous study. However, the previous studies trained the pigs within small groups of not more than 12 sows and used an electronic feeding station which could identify pigs at the entrance. In addition, they did not report the effect of the training itself on lesion incidence. The present study was conducted to validate the earlier results at a conventional livestock farm. Here, the training was performed within a group of up to 35 sows and with a feeding station which identified sows at the trough only. The training of the whole group required, in total, 180 days. First results show that signal feeding works under common practical conditions but might lead to more skin lesions during the period of transitioning from conventional electronic feeding to signal feeding. The associated higher level of aggressive encounters had however no significant effect on the rearing performance. Continued observations of further gestations will show whether the consolidation of the conditioning leads to a general reduction of aggressive encounters especially at group mixing. This might result in an easier integration of younger sows, which could be associated with an increased conception rate or improvement of the breeding results and would make signal feeding cost-effective in practical applications.

Keywords: signal feeding, automated operant condition, group housing, gestating sows

Introduction

Signal feeding (Manteuffel *et al.,* 2011) is a feeding technology that uses automated operant conditioning for individual acoustic signals to provide cognitive enrichment to group housed pigs (Ernst, 2008; Zebunke *et al.,* 2013) and reduce feeding associated aggression in sows (Kirchner *et al.,* 2012). The latter suggests that signal feeding can be used to improve housing conditions for group housed gestating sows. However, until now it has only been evaluated with small groups of pigs or in a highly enriched environment using a feeding station type that could identify pigs already in front of its entrance. In addition, long term economic effects justifying the additional investment for signal feeding are still unknown.

This paper presents first results of a study implementing signal feeding at a commercial pig breeding farm. The study aim is to quantify the economic effects of signal feeding under practical conditions. For the first time the operant conditioning is performed within a large group of sows using a commercial feeding station able to identify pigs at the trough alone. The current results relate to the first phase of the validation where a gestation group underwent the transition from conventional electronic sow feeding (ESF) to signal feeding. To determine the effectivity of signal feeding in the given setup, wound scores were collected and the duration of the training progress was recorded.

Methods

Animals and housing conditions

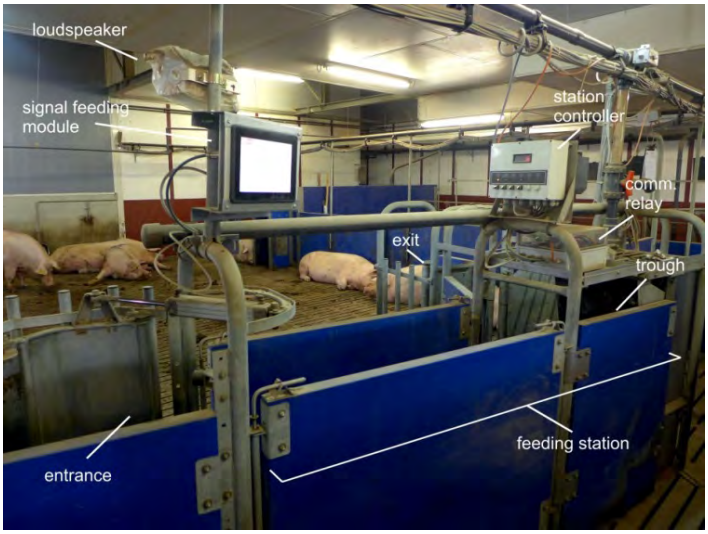

Figure 1. Feeding station and signal feeding equipment. The pia-SF signal feeding module is the touch panel PC mounted above the entrance. The communication relay incorporates networking equipment and an embedded PC for transferring information between the station controller and the signal feeding module

The study was conducted in a conventional commercial pig breeding farm with Danish Landrace × Danish Yorkshire (F1) sows. The sows were housed on partly slatted concrete floors in gestation pens structured with walls into bays and a main area. The pens were furnished according to current legal regulations and equipped with Callmatic electronic sow feeding (ESF) stations for liquid feed (Big Dutchman AG, Germany) (Figure 1). One gestation pen was additionally equipped with the upgrade module for signal feeding (pia-SF, pironex GmbH, Germany). The pigs stayed from the 2nd until the 110th day of gestation in groups of about 35 sows in the compartment. Their age ranged from 2nd to 6th gestation. The ESF control group was a gestation group with an offset of one week in the production cycle housed in the same compartment.

Training procedure

All 35 sows of the signal feeding gestation group were fed at one single station simultaneously. This means naïve sows could acquire feed by spontaneous visits to the feeding station (ESF), already conditioned sows were only fed after they have been called (signal) and some sows had the chance to get fed both ways (training). During the transition of the group to signal feeding the number of naïve ESF sows continuously reduced while the number of signal feeding sows within the group increased. The operant conditioning to individual acoustic signals was performed within the group of 35 sows for up to eight training sows. The sows were selected based on their social rank starting with medium ranked sows. This approach ensured that the sows in training had a sufficiently high rank to visit the feeding station more than once per day but not that high that they would block the access for other sows completely. The training was aborted if the sow did not retrieve feed for more than 24 h. It was finished successfully if the sow reached a precision of more than 40% or the training lasted longer than 16 days. When the training was stopped for one sow it was started for another ESF sow. Sows that were considered conditioned

but did not retrieve feed for more than 24 h were put back into training mode. Hence the ability to retrieve feed was taken as ultimate benchmark for a successful conditioning. The training was conducted as a mix of spontaneous and scheduled feed access. During the first four days of training a Pavlovian condition was performed to accustom the sows to their signals. The time share for spontaneous feed access opportunities was reduced gradually depending on the individual learning progress of the sows to ensure sufficient feed supply during the training (Manteuffel *et al.*, 2011). In order to ensure feed access for naïve low ranking sows, calling a sow for scheduled feeding was aborted if a naïve sow with remaining feed was detected within the station. Because it was anticipated that the training procedure involves an increased stress burden, the training of naïve sows started after the 28th day of gestation, when the conception was secure. At this time also sows not pregnant were removed from the group. Sows were called for feeding from the first day on if they were considered conditioned.

Data analysis

Information on the number of naïve and trained sows was automatically recorded by the signal feeding software. Wound scores were obtained by visual inspection of the sows in the signal feeding group and the ESF control group using the definitions of an earlier trial (Kirchner *et al.*, 2012). The breeding results were taken from the regular documentation of the farm. Statistical analyses were performed using SAS/STAT software, Version 9.4 of the SAS System for Windows using the GLIMMIX procedure (SAS Institute Inc. 2012). For the count response variables (born alive, dead at Day 1, dead until Day 28) a Poisson model (distribution = Poisson, link = log) was used with the fixed effect treatment (ESF, signal). The count response variable (wound score sum) was analysed for the fixed effects repetition (1-3), age (2nd-3rd gestation, > 3 gestations), treatment (ESF, signal), time in days (5, 22, 43, 64, 92) and their interactions. Repeated measures on the same animal were taken into account by the residual option in the random statement.

Results

Figure 2 depicts the training progress for the 28-35 sows of the signal feeding group. During the operant conditioning the sows had to learn to use their acoustic signal as an indication for feed access by entering the feeding station more frequently and testing if they get fed. All sows of the group were successfully conditioned to individual acoustic signals after a total of 180 days. Completing the operant conditioning for a single sow effectively took between 20–30 days. This was considerably longer than previously observed for small groups (Manteuffel *et al.*, 2010).

The transition to signal feeding tended to increase the wound score sum in general (treatment: $F_{1,94} = 3.37$, $P = 0.069$). This was evident, especially at the end of the gestation (gestation day × treatment: $F_{4,328} = 7.31$, $P < 0.001$), where more and more sows passed through the training procedure but had not consolidated their conditioning yet (Figure 3 / $t_{328} = 3.67$, $P < 0.05$). In addition, younger pigs had in general a higher wound score sum (age: $F = 9.3$, $P < 0.05$) and the wounds reduced during the gestation in both groups (gestation day: $F_{4,328} = 50.51$, $P < 0.001$). The analysis of the wound score showed significant repetition effects ($F_{2,93} = 16.52$, $P < 0.001$) in both the control and the signal feeding group.

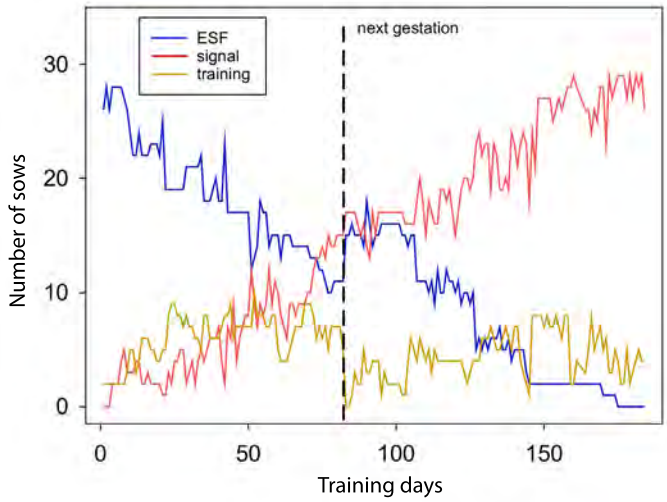

Figure 2. Training progress within two gestation periods. The *ESF* curve represents the number of naïve sows. Additional naïve replacement sows enter the group with the start of the second gestation period. The *signal* curve represents the number of sows performing signal feeding, while the *training* curve indicates the number of pigs currently conditioned

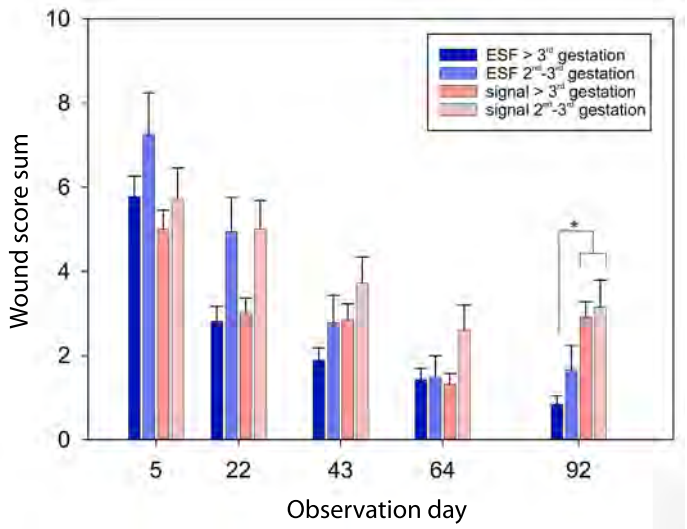

Figure 3. Sum of wound scores depending on pig age and duration of gestation. *ESF* bars represent score sums of a control group fed by conventional ESF. *Signal* bars include score sums of all sows in the signal feeding group regardless of their training status. Lighter colours represent pigs with less than four gestations

The increased wound score sum indicates more aggressive encounters and hence an increased stress burden for the signal feeding group during the training. However, this did not affect the breeding results of this group. Both the signal feeding and the conventional ESF group yielded identical numbers of piglets born alive and losses during birth and lactation (Figure 4).

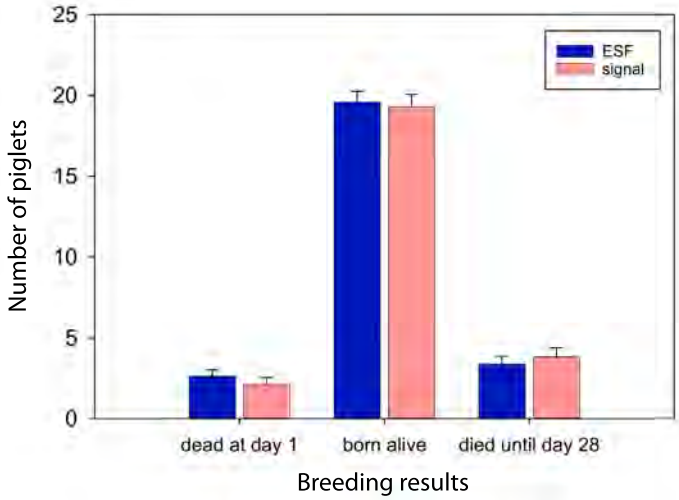

Figure 4. Average rearing performance for the two gestation periods required for the transition to signal feeding. *EFS* bars represent the results of the separate ESF control group. The *signal* bars include the breeding results of all sows in the signal feeding group regardless of their training status

Discussion

The study shows that it is possible to perform an operant conditioning of adult sows for individual acoustic signals under the conditions of intensive livestock farming. However, the training took considerably longer than in previous studies with a different station type and smaller groups (Manteuffel *et al.*, 2010; Kirchner *et al.*, 2014). This finding is consistent with previous results, which found a reduction and slower improvement of the sows' classification competence when they were moved from a small to a large group (Manteuffel *et al.*, 2013). Presumably, the reaction of the conditioned sows is more encumbered the larger the group becomes, because more high ranking sows occupy the feeding station (Manteuffel *et al.*, 2010) or perform blank visits without feed allowance. Beside rank effects, effects from the liquid feeding system might have contributed to a prolonged training. The delay between detecting a sow in the station and feed dispersion with the liquid feeding system could be more than 30 s depending on whether feed was available in the pipes or the system was just flushed for cleaning. In addition, the original training procedure had to be altered to alleviate the feeding of naïve young sows. In contrast to previous studies, the present study indicates that ongoing calls of sows could be aborted regardless of their reaction to allow the feeding of naïve sows that entered the station during the call. This variation in behaviour outcome leads to a partial extinction of the conditioning and thus, a longer duration until the conditioning is consolidated (Bouton, 2002).

Earlier studies found fewer agonistic interactions and a reduced number of severe wounds with signal feeding than the present study (Kirchner *et al.*, 2012). There are many possible reasons for this difference. The feeding station utilised with the previous studies had an animal identification at the entrance. Hence, the pigs could determine their feed access much quicker and without the need to prevail over a group of other sows also wanting to enter the station. In addition, the training was conducted in smaller and more homogenous groups of younger sows at a separate training station.

The results show significant repetition effects for the wound score. This was anticipated for the signal feeding group because the predominant feeding procedure changed from

ESF to calls during the study. However, repetition effects were not expected for the control group. The cause could lie in factors which affected both groups, as mainly in repetition three more injuries than previously occurred. A plausible cause could be weather related changes in the average compartment temperature. Another factor could be outages of the liquid feeding system, which occasionally occurred in all repetitions but might have different effects depending on their precise timing.

In the present study, with booth feeding regimes, younger pigs were more affected by agonistic interactions. This was probably due to their lower rank which made them more often the target of attacks (Hoy *et al.,* 2009). Once the signal conditioning is well established, a reduction of queuing behaviour at the station can be expected especially of experienced older sows with higher social ranks (Kirchner *et al.*, 2012). This should in the long term reduce the wound score of younger sows and improve their feed access. The further course of this study will show whether this will reduce the amount of work entailed in the integration of young sows. At the same time, effects on the conception rate and on breeding results will be evaluated to quantify the economic effects from using signal feeding.

Conclusion

First results from this ongoing study show that a transition from conventional electronic sow feeding to signal feeding can be completed in a reasonable time frame. In contrast to earlier studies, the present study found more lesions in sows from the signal feeding group during this transition phase. A reason for this finding could be a more challenging learning task and a prolonged training. No significant effect from the higher lesion score on the rearing performance was found. The further course of the study will show whether a well-established signal feeding system and a consolidated conditioning of the sows will reduce queuing behaviour and feeding related agonistic interactions. This could ease feed access especially for younger replacement sows. Such an effect would reduce the work load for the staff and might improve the conception rate and the rearing performance of younger sows. This will form the basis for a detailed analysis of the economic viability of signal feeding.

Acknowledgements

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References

Bouton, M.E. (2002). "Context, ambiguity, and unlearning: sources of relapse after behavioral extinction." *Biological psychiatry*, 52(10): 976–986.

Ernst, K. (2008). Erfolgreiche Bewältigung kognitiver Herausforderungen und ihre Konsequenzen auf ethologische und physiologische Parameter bei Schweinen (Sus scrofa domestika) (Effects of

successful mastering cognitive challenges on ethological and physiological parameters in pigs.), Doctoral dissertation, Deutsche Nationalbibliothek, https://d-nb.info/996933344/34.

Hoy, S., J. Bauer, C. Borberg, L. Chonsch and C. Weirich (2009). "Investigations on dynamics of social rank of sows during several parities." *Applied Animal Behaviour Science,* 121(2): 103–107.

Kirchner, J., C. Manteuffel, G. Manteuffel and L. Schrader (2014). "Learning performance of gestating sows called to the feeder." *Applied Animal Behaviour Science,* 153: 18–25.

Kirchner, J., G. Manteuffel and L. Schrader (2012). "Individual calling to the feeding station can reduce agonistic interactions and lesions in group housed sows." *Journal Animal Science,* 90: 5013–5020.

Manteuffel, C., J. Kirchner, L. Schrader, P. Schoen and G. Manteuffel (2013). Call feeding gestating sows in larger groups. Precision Livestock Farming '13. B.D. a. V.J. Leuven**:** 9.

Manteuffel, C., P.C. Schön and G. Manteuffel (2011). "Beyond electronic feeding: The implementation of call feeding for pregnant sows." *Computers and Electronics in Agriculture,* 79(1): 36–41.

Manteuffel, G., A. Mannewitz, C. Manteuffel, A. Tuchscherer and L. Schrader (2010). "Social hierarchy affects the adaption of pregnant sows to a call feeding learning paradigm." *Applied Animal Behaviour Science,* 128(1-4): 30–36.

SAS Institute Inc. (2012). SAS/STAT® 9.4 User's Guide. SAS Institute Inc. Cary, NC.

Zebunke, M., B. Puppe and J. Langbein (2013). "Effects of cognitive enrichment on behavioural and physiological reactions of pigs." *Physiology & Behavior,* 118: 70–79.

Session 14

Location and Tracking of Animal Movement (2)

Developing new training cues for virtual fencing

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Abstract

A suitable virtual fencing system could improve pasture management and decrease labour and costs. However, recent research has shown that cows need training in order to be able to understand the virtual fencing mechanism. To improve the understanding of the cows it was envisaged to develop a new approach that supports the learning process. As cows rely more on visual cues than on audio signals, we set out to look into the possibility to use visual cues at least for training purposes. A first prototype with dual warning signals, based on audio and visual cues was developed. The idea behind it was to form a cue consequence association between the audio cue and the electric stimulus by temporarily supporting the learning efforts using visual cues. Therefore, a system based on a raspberry pi platform was developed. As a network and communication with a higher number of devices is paramount, the message queuing telemetry transport protocol was used. This protocol is particularly suitable for machine-to-machine communication through the 'publish/subscribe' functionality. Based on theoretical considerations and pretests, a possible luminaire design was created and simulated with a simulation software. A first prototype was built and tested under different light conditions. The system has shown initial promise. However, as the visual cues do not work in sunlight, the next step will be to develop an automated learning system, which could be used between dusk and dawn.

Keywords: dairy cows, visual cues, prototype, light conditions

Introduction

A suitable virtual fencing system could improve pasture management and decrease labour and costs. However, recent research has shown that cows need training in order to be able to understand the virtual fencing mechanism (pers. experimental Obs. and unpublished data). To improve the understanding of the cows it was envisaged to develop a new approach that supports the learning process. As cows rely more on visual cues than on audio signals (Moran & Doyle, s.a.), we set out to look into the possibility of using visual cues at least for training purposes.

Conventional fencing, especially in difficult terrain, such as in the Alps, is expensive and labour intensive. A low energy-consuming virtual fencing device could reduce these costs significantly, if it was possible to train animals in such a way, that the triggering system is as effective as a conventional fixed or electric fence (Umstatter, 2011). Moreover, to locate the animal and to transfer data connected with the animal, such as locomotive or feeding activity, to a server could be an additional benefit of such a device. Particularly in extensive systems, a monitoring system for health and welfare can reduce the workload of a farmer considerably.

A virtual fence can be defined as a structure serving as an enclosure, a barrier, or a boundary without a physical barrier (Umstatter, 2011). So far, most research has been carried out developing different prototypes of virtual fencing based on a combination of audio warning cues and electric stimuli (Campbell *et al.,* 2019; Umstatter, 2011). In most

cases, the electronic device consists of a collar with integrated GPS to track animals and a triggering system to control and guide them. The system determines the actual position of the cow. If the animal tries to cross the predefined virtual border, the system first triggers a warning cue and if the animal proceeds, the system triggers an aversive stimulus. Often GSM (Global System for Mobile Communications) technology is used to communicate with the collar to redefine virtual boundaries and can be almost labour free. The aim of virtual fencing is to control and guide cattle without using conventional fencing in order to save labour and material costs.

Research so far carried out was based on the analysis of different warning cues and aversive stimuli (Lee *et al.*, 2009; Umstatter *et al.*, 2009; Umstatter *et al.*, 2013) and has also shown that it is key for animal welfare to develop a training system as the animals need to learn how the systems works.

Therefore, we set out to develop a virtual fencing system with dual warning cues, based on audio and visual cues. As cattle can have greater difficulty in locating the origin of sounds, they will use their sight to assist them to determine the source (Moran & Doyle, s.a.). Thus, the aim was to a) scope out the technical options for such a system and b) to investigate how dairy cows respond to visual cues. The objective in the longer-term is to investigate if visual cues can help to teach cows how a virtual fencing system works.

Material and methods

Prototype

A first prototype collar with dual warning signals, integrating audio and visual cues, was developed. Based on theoretical considerations and pretests, a possible luminaire design was created and simulated with the simulation program OpticStudio® (Zemax, LLC, USA; Figure 1). Technical limitations for the luminaire had to be accounted for as the system had to be integrated into a collar. Limiting factors such as size, cooling system and power supply had to be taken into account for the choice of lamp design.

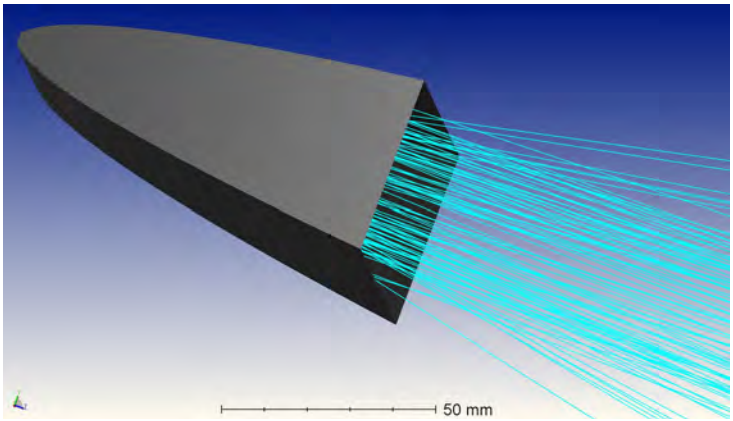

Figure 1. Light source simulation created with the software OpticStudio® (Zemax, LLC, USA)

The lamp was designed in the shape of a parabolic mirror and made of aluminium sheet as seen in Figure 2. The mirror had its focal point at 1 mm and an opening of 200 mm. Eleven LEDs with 1 W electrical power each and 110 lm luminous flux were used and mounted in the focal point. A reasonable thermal management and a mobile power supply in the desired device size were possible with electrical power of 11 W.

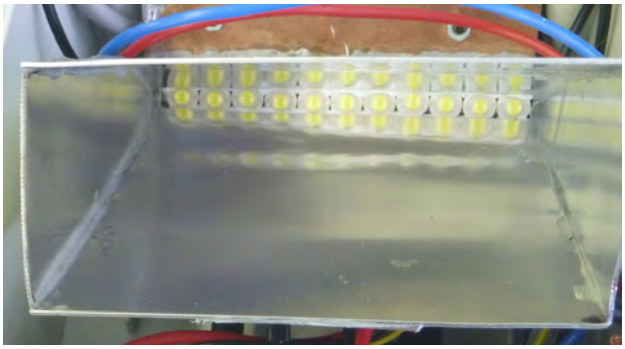

Figure 2. The luminaire design of the prototype with 11 LEDs

An evaluation process was then carried out to select a suitable prototyping platform. Established prototyping platforms such as the open source platforms Arduino (Arduino cc. Italy), Beagle Bone (BeagleBoard.org Foundation, Michigan, USA), and Raspberry Pi (Raspberry Pi Foundation, Great Britain) were examined and compared with rugged and high quality products from Toradex (Toradex AG, Switzerland). Different requirements such as the possibility of wireless communication, operating system, size, energy consumption, audio and video signals and price were evaluated (Table 1) and graded. The grading system ranged from one to five, with one being the lowest score (least suitable) and five being the highest (most suitable).

The ability of the selected prototyping platform to network and communicate with a larger number of devices was paramount. For this type of network, the message queuing telemetry transport protocol was used. It is particularly suitable for machine-to-machine communication due to the 'publish/subscribe' functionality.

A first prototype was then built and tested under different light conditions to gather information on its suitability for an animal experiment.

Test of luminaires

Five luminaires were tested under controlled conditions. The trial environment had no relevant light sources with measurements showing 0 lx. The luminaires were put parallel with a distance of 1 m to the sensor, as seen in Figure 3, and were switched on for 30 s before measurements were taken. The aim of this test was to give a rough assessment of suitability, no standard deviation was determined.

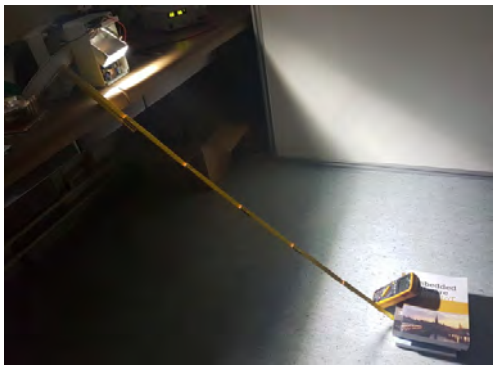

Figure 3. The test setup for luminaires under controlled conditions

Results and discussion

As a result of the analysis of available prototyping platforms (Table 1), Raspberry Pi 3 was chosen, as this system is well suited for both operating audio and visual cues. Moreover, it is sufficiently flexible so that it can also be used if the system or the number of components needs to be expanded in future.

Furthermore, it was necessary to create a luminaire, which can produce a strong visible line on the ground. The development phase identified challenges, which need to be overcome. The test of different luminaires highlighted the importance of taking the luminaire optics into account as the illuminated area has a high impact on the illuminance (Table 2). The greater the illuminated area, the more the illuminance is reduced when using the same electrical power.

The last tested luminaire (11 W LED) was developed after the measurements of the former luminaires were taken and showing an illuminance of 1,080 lx with 11 W and 110 lm. This demonstrated that with a suitable mirror a stronger line could be produced. However, due to technical limitations such as size, cooling system and power supply, no stronger visual line could be achieved. In Figure 4 a prototype collar is shown exhibiting the visual line which could be used as a cue for cattle.

Table 1. Comparison of potential candidates for the prototyping platform

Requirements	Arduino UNO	Arduino Zero	Raspberry Pi	Beagle Bone	Toradex Products
Wireless communication IEEE 802.11 (WLAN)	2	2	5	4	5
Operating System (Linux preferred)	1	2	5	5	5
JavaTechnology (JRE)	1	1	5	5	5
Accessible GPIO and library for easy use	5	5	5	5	5
Audio output (analogue)	2	2	5	2	5
Monitor output (analogue/ digital)	1	1	5	1	5
Energy consumption (low)	5	5	2	2	2
Size (small)	5	5	4	4	3
Price - performance	5	4	3	2	2
Online help / community/ libraries / tutorials / example projects	5	4	5	4	3
Expandability	4	4	5	4	4
Total	3.3	3.2	4.5	3.5	4.2

Table 2. Comparison of illuminance of different luminaires. The luminaire 11 W LED (in bold) was developed as a result of the former measurements and was used in the prototype

Luminaire description	Manufacturer	Illuminance
50 W Low voltage halogen bulb with reflector (round)	BAUHAUS Fachcentren AG	4,000 lx
10 W LED with parabolic mirror from garden light (round)	Self-development	550 lx
30 W LED with self-made parabolic mirror (oblong)	Self-development	835 lx
100 W LED with self-made parabolic mirror (oblong)	Self-development	3,060 lx
11 W LED with self-made parabolic mirror (oblong)	Self-development	1,080 lx

On a bright summer day around 100'000 lx can be measured, at a cloudy summer day 20'000 lx and in the shade in summer 10'000 lx (Rindergesundheitsdienst Schweiz, s.a.). The same source states that at a cloudy winter day we can find about 3'500 lx and in full moon 0.25 lx. Therefore, the developed luminaire will not work in sunlight.

However, there are circumstances when visual cues could be used. It is an option to develop a training system, which for example might be used at night for training purposes. The idea behind it is to form a cue consequence association between the audio cue and the electric stimulus by temporarily supporting the learning efforts using visual cues. After a training period the visual cues could be stopped and the cows have to rely purely on audio cues. Intermittently refresher trainings could be envisaged to maintain a good cue-consequence association. A continuous use of visual cues has also the disadvantage that additional power needs to be provided. It should therefore be seen as a support for training purposes.

Figure 4. Prototype of a virtual fence with an integrated visual cue system

The next step of this research will involve different visual cues being presented to cows in a behavioural experiment in order to gather information on their responses. For the first trial, a projector will be used in a defined space where the amount of lux can be controlled. One of the visual cues to be presented is shown in Figure 5.

Figure 5. Projected line onto a rubber surface in a dairy shed, which will be used for animal behaviour trials testing visual cues

Conclusions and Outlook

The prototype system has shown some promise. However, as the visual cues do not work in sunlight, the next step will be to develop an automated learning system, which could be used between dusk and dawn. Dairy cattle trials will shed some light into the responses of animals to different visual cues. As a next step, the responses of dairy cows to different visual cues, from a solid line to a flashing line, will be tested. Furthermore, the developed prototype will also be tested on dairy cows.

Acknowledgements

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References

Campbell, D.L.M., Haynes, S.J., Lea, J.M., Farrer, W.J. and Lee, C. (2019). Temporary Exclusion of Cattle from a Riparian Zone Using Virtual Fencing Technology. *Animals* 9(5), URL: https://doi.org/10.3390/ani9010005.

Lee, C., Henshall, J.M., Wark, T.J., Crossman, C.C., Reed, M.T., Brewer, H.G., O'Grady, J. and Fisher, A.D. (2009). Associative learning by cattle to enable effective and ethical virtual fences. *Applied Animal Behaviour Science*, 119, 15–22.

Moran, J. and Doyle, R. (s.a) *Cow Talk - Understanding Dairy Cow Behaviour to Improve Their Welfare on Asian Farms.* Available at: URL: http://www.publish.csiro.au/ebook/chapter/9781486301614_Chapter4. Accessed: 1st of March 2019.

Rindergesundheitsdienst Schweiz (s.a.) *Licht* URL: http://www.gesunderinder.ch/Allgemeines/Stallklima/Licht.aspx . Accessed: 1st of March 2019.

Umstatter, C. (2011). The evolution of virtual fences: A review. *Computers and Electronics in Agriculture* 75, 10–22.

Umstatter, C. Brocklehurst, S., Ross, D.W. and Haskell, M.J. (2013). Can the location of cattle be managed using broadcast audio cues? *Applied Animal Behaviour Science* 147, 34–42.

Umstatter, C., Tailleur, C., Ross, D. and Haskell, M.J. (2009). Could virtual fences work without giving cows electric shocks? In: Lokhorst, C. and Groot Koerkamp, *P.W.G. (eds.), Precision Livestock Farming `09*, Wageningen Academic Publishers, Wageningen, NL, 161–168.

Localisation and accelerometer sensors for the detection of oestrus in dairy cattle

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Abstract

The aim of this work was to combine ultra-wide band (UWB) localisation tracking, a neck-mounted accelerometer and a leg-mounted accelerometer for the detection of oestrus in dairy cows. Twelve Holstein cows with successful artificial insemination (AI) were used in this study. The sensors were attached two weeks before the expected day of oestrus and removed after AI. Different cow variables (e.g. lying time, number of steps, ruminating time, travelled distance) were extracted from the raw sensor data and used to build and test the detection models. Logistic regression models were developed for each individual sensor as well as for each combination of sensors (two or three). The performances were similar when one sensor was used only as when combining the neck- and leg-mounted accelerometer (sensitivity (Se) =75-78%, area under curve (AUC) =93-94%). The performance increased when localisation was combined with either the neck- or leg-mounted accelerometer, especially for the sensitivity (80% for leg accelerometer + localisation and 88% for neck accelerometer + localisation). The AUC were nearly the same (97%). The best performance was obtained with the combination of all three sensors (Se = 90%, AUC = 99%). Future work will consist of expanding this research to other herds with larger sample size as well as considering cows' anomalies (e.g. mastitis, lameness) and other sensors (e.g. bolus or eartag to measure the temperature).

Keywords: Accelerometer, UWB localisation system, dairy cows, machine learning, K-mean, support vector machine, behaviours classification, oestrus, internet-of-animals

Introduction

The profitability of dairy farms depends greatly on the breeding efficiency of dairy cows and the timely detection of oestrus (De Vries, 2010). Without accurate detection of oestrus in artificial insemination (AI) breeding programs, mistakes can be made and costs can be elevated due to wasted straws of semen, technician costs and time. In addition, numerous studies have documented that additional days in which cows are not pregnant beyond the optimal time post-calving are costly (Groenendaal, Galligan, & Mulder, 2010; Meadows, Rajala-Schultz, & Frazer, 2010). Ultimately, accurate oestrus detection should be used to successfully breed cattle with AI. However, visual detection of oestrus becomes difficult in large sized herds, as the cows may not show visual signs of oestrus (e.g. restlessness, standing to be mounted) during the time visual observation is being performed due to the impact of stress and other diseases (e.g. lameness).

To manage oestrus detection in high density livestock farms, farmers increasingly rely on automated systems using sensors for the collection and the interpretation of animal data. Several studies have investigated a variety of sensors (pressure, activity meters, video cameras, recordings of vocalisation, measurements of body temperature and milk progesterone concentration) for oestrus detection (Reith & Hoy, 2018; Roelofs, López-

Gatius, Hunter, van Eerdenburg, & Hanzen, 2010; Stevenson, 2001). On the basis of their review, Reith and Hoy (2018) recommended to give highest priority to the detection based on sensor-supported activity monitoring (e.g. accelerometers) as being the most successful tools for automated oestrus detection. Meanwhile, the increasing availability of positioning systems based on small devices unlock the potential of using real-time animal location data for the benefit of cow and farmer. Although recent studies (Homer *et al.*, 2013; Porto, Arcidiacono, Giummarra, Anguzza, & Cascone, 2014; Tullo, Fontana, Gottardo, Sloth, & Guarino, 2016) started to involve positioning data for the monitoring of dairy cows, localisation sensors were never combined with neck- and leg-mounted accelerometers for oestrus detection up to now. This will likely increase the detection accuracy by expanding the range of predictor variable and allow automated alerting to the farmer for a wider range of issues (not only oestrus) that require his action or attention as compared to systems based on one sensor.

In the present study, ten cow variables were extracted from three sensors (i.e. neck- and leg-mounted accelerometers and localisation sensor). Three variables were extracted from each accelerometer (e.g. ruminating time, feeding time, and resting time from the neck-mounted accelerometer, lying time, lying bouts, and number of steps from the leg-mounted accelerometer), and four variables were extracted from the localisation data (i.e. travelled distance, time in cubicles, time in feeding zone, time in drinking zone). These variables were reported previously as a good predictor for oestrus detection (Pahl, Hartung, Mahlkow-Nerge, & Haeussermann, 2015a; Reith, Brandt, & Hoy, 2014). This work is the first to investigate combining a neck-mounted accelerometer, a leg-mounted accelerometer, and a localisation sensor for the detection of oestrus in dairy cattle.

The use of a combination of sensors is likely to increase the detection accuracy by expanding the range of predictor variables and allow automated alerting to the farmer of a wider range of issues in addition to oestrus (e.g. lameness, calving) that require his action or attention as compared to systems based on one sensor. Moreover, smart communication between multiple sensors may considerably reduce the power consumption as compared to each sensor operating independently of one another. For example, when detecting a cow in lying down position by the leg-mounted accelerometer, the localisation sensor could be turned-off until the cow has changed position. This could save more than 50% of the energy of the position monitoring, since cows spend 12–14 hours per day lying down (Gomez & Cook, 2010).

Material and methods

Animals and housing

In total, 12 cows (parity 2.8 ± 1.3) with successful insemination were used for the detection of oestrus events. The cows were housed with other cows (31 in total) in a free-stall barn of the Flanders Research Institute for Agriculture, Fisheries and Food (ILVO), Melle, Belgium. The barn contains four areas of 30 m long and 13 m wide each, with individual cubicles and a concrete slatted floor. The cubicles (n = 32, width 115 cm, length from curb to front rail 178 cm, front rail height 70 cm, neck rail height 109 cm, neck rail distance from curb 168 cm) were bedded with a lime-straw-water mixture. The cows were fed roughage ad libitum. The concentrates were supplied by computerised concentrate feeders. Drinking water was available ad libitum (two drinking troughs). This study was conducted between September 2017 and April 2018.

Sensors

Each cow was fitted with three sensors: a localisation node, a leg-mounted accelerometer (right hind leg), and a collar-mounted accelerometer (Figure 1). For the localisation data, an

OpenRTLS ultra-wide band (UWB) localisation system (DecaWave, Ireland) was installed in the barn using seven anchors (including the master anchor). The sampling rate of the localisation system was set to 2 Hz to enable a logging interval of about four weeks. Accuracy measurements were performed beforehand. A localisation node was put in 46 different locations in the cubicles and the alley. Then, a comparison was made between the actual locations and locations estimated by the localisation system. The mean and median accuracy were 38 and 34 centimetres. The acceleration data (i.e. three orthogonal accelerometer vectors) were logged with a sampling rate of 10 Hz (10 samples each second) using Axivity AX3 loggers (Axivity Ltd, Newcastle, UK). The clocks of the localisation system and the accelerometers were synchronised at the start of the experiments.

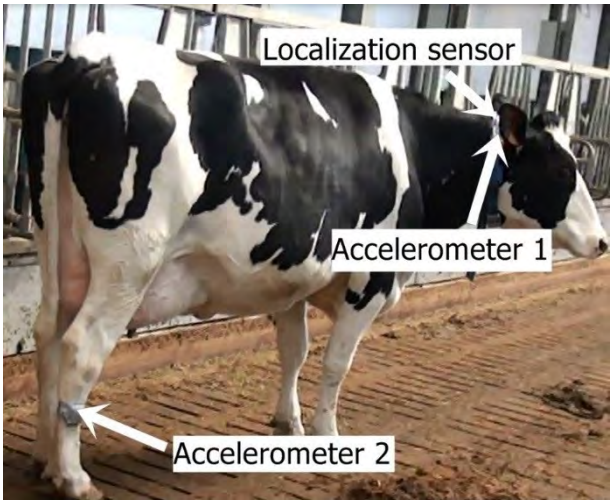

Figure 6. A cow wearing the three sensors

Data collection procedure

The sensors were attached two weeks before the expected day of oestrus and removed after the AI. Decisions about timing of insemination were made by the ILVO stock people. Not all inseminations were associated with real estruses as insemination might be performed on the basis of a false alert or erroneous interpretation of a cow's behaviour. Therefore, to ensure that the data-set was based on true cases of oestrus, only data from periods around inseminations that led to confirmed pregnancy were used in this study. From 15 cows, 12 cows with successful insemination were used to create the dataset.

Processing of sensors data

The data processing was performed using MATLAB software (Release 2018b, The MathWorks, Inc., Natick, Massachusetts, United States).

In total, three variables were extracted from each accelerometer (i.e. hourly ruminating time, feeding time, and resting time from the neck-mounted accelerometer, and hourly lying time, lying bouts, and number of steps from the leg-mounted accelerometer).

As presented in Benaissa *et al.* (2018), the data of the neck-mounted accelerometer were used to obtain ruminating, feeding, and resting times. We note here that resting behaviour is when the cow has a static position (inactivity), i.e. either standing or lying. Lying bouts and lying time were extracted from the leg-mounted accelerometer as presented in (Ito, Weary, & von Keyserlingk, 2009). Finally, a simple k-Nearest Neighbours (kNN) algorithm

was developed and validated (accuracy of 97% compared to direct observations) to count the number of steps based on the data of the leg-mounted accelerometer.

In total, four variables were extracted from the localisation data for each one-hour time interval (i.e. travelled distance, time in cubicles, time in feeding zone, time in drinking zone). The travelled distance is the sum of all distances that are labelled as walking, along the trajectory. A distance between two location updates is labelled as such if the travelled distance exceeds a threshold within a certain interval. When a cow is located within the lying zone, e.g. the cubicles, a first timer is started. When this timer exceeds a hold-off time (i.e. one minute), the real lying timer starts. The purpose of the first timer is to remove false positives (e.g. when a cow is falsely located in the boxes for a short time). The timer stops when the cow is located outside the boxes for the same hold-off time. The times at drinking zone and feeding zone were calculated with the same procedure as time in lying cubicles but with another zone label. These zones are rectangles (or more generally polygons) that have to be specified once and can be drawn on the floor plan or defined in a text document.

Detection models

Since the aim was to build a model for binary classification (e.g. a cow is in oestrus or not), logistic regression was chosen. Also, logistic regression is widely adopted when interested in the impact of various variables (variables from different sensors in this case) on a response variable (Sperandei, 2014). All variables (feeding time, number of steps, lying time, etc.) were summarised in 1-h intervals. The 1-h intervals were adjusted relative to the time of the actual AI (0 is the time of AI) only one week before AI was used for the detection models, as the first week was considered a habituation period. A 24 h moving average was applied to smooth the data as performed in (Borchers *et al.*, 2017). To estimate the changes over time of the cow variables, each value of the calculated hourly variables was subtracted from the mean value of the past 24 values of the same cow (*i.e.* 24 hours) as presented in (Rutten *et al.,* 2017). Any alerts during hours -1 to -24 were treated as true positives. Finally, to measure the performances of the detection models, the leave one out cross validation strategy was used (Arlot & Celisse, 2010) to calculate the precision, the sensitivity, the specificity, the overall accuracy, and the area under curve (AUC). The data of one cow were used as a testing set and the data of the remaining cows were used as a training set. This was repeated for all cows in the data set and the average precision, sensitivity, specificity, and overall accuracy were considered.

Results and discussion

For the neck-mounted accelerometer, ruminating time decreased by 26% ($P < 0.01$) between the reference period (i.e. six days before the day of oestrus) and the day of AI. Similarly, resting time decreased by 23% ($P < 0.01$). However, feeding time did not show a significant change ($P > 0.05$). For the leg-mounted accelerometer, the lying time decreased by 38% ($P < 0.01$) and the number of steps increased by 95% ($P < 0.01$), while lying bouts did not change significantly ($P > 0.05$). Finally, for the localisation sensor, the travelled distance increased by 92% ($P < 0.01$) and the time in cubicles decreased by 32% ($P < 0.05$). The change was not significant ($P > 0.05$) for both the time in drinking zone and in feeding zone. In comparison to other studies, Dolecheck *et al. (2015)* found that lying time decreased during the oestrus period by 58%. Time spent lying and resting time decrease around oestrus because of increased activity and restlessness (Jónsson, Blanke, Poulsen, Caponetti, & Højsgaard, 2011). This explains also the decrease of resting time. Ruminating time in our study decreased during oestrus by 37%. Reith and Hoy (2012) evaluated 265 oestrus events, finding that ruminating time on the day of oestrus decreased by 17% (74 min), but with large variation between herds (14–24%). In a follow-up study that looked

at 453 oestrous cycles, ruminating time decreased by 20% (83 min) on the day of oestrus (Reith *et al.*, 2014). Pahl *et al.* (2015) also found a decrease in ruminating time (19.3%) on the day of AI. The decreases in ruminating time around oestrus found in the current study (26%) is comparable to previous studies, although a small number of cows was considered. The change in feeding time was not significant, similar to the conclusions reported by De Silva *et al.* (1981), who found no change in feed intake during the 3 d period around oestrus.

Table 1. Mean values and standard error (SE) of the cow variables obtained by the three sensors, [-24, 0] is the 24 hours before the AI (*$P < 0.05$, **$P < 0.01$, no asterisks means $P > 0.05$)

Sensors	Variables	[-168,-24]	[-24,0]	Difference	
Neck accelerometer	Ruminating time [hours]	8.4±0.6	6.2±0.7	-2.2**	-26%
	Feeding time [hours]	4.5±0.5	5.1±0.3	0.6	13%
	Resting time [hours]	7.3±0.7	5.6±0.5	-1.7**	-23%
Leg accelerometer	Lying bouts [-]	6.8±1.2	6.1±0.8	-0.7	-10%
	Lying time [hours]	12.0±0.9	7.4±1.1	-4.6**	-38%
	Number of steps [-]	2,470±210	4,824±302	2,354**	95%
Localisation	Travelled distance [m]	2,161±165	4,146±285	1,985**	92%
	Time in cubicles [hours]	10.5±0.8	7.1±1.0	-3.4*	-32%
	Time in feeding zone [hours]	4.8±0.5	4.9±0.4	0.1	2%
	Time in drinking zone [min]	14.4±10.6	19.1±13.2	4.7	32%

Detection performance for oestrus is listed in Table 2. Similar results were obtained when using one sensor as compared to combining neck- and leg-mounted accelerometers (Se = 75-78%, AUC = 93-94%). In both cases, the overall accuracy was around 95%. The performance increased when localisation with either neck- or leg-mounted accelerometer was combined, especially for the sensitivity (80% for leg accelerometer + localisation and 88% for neck accelerometer + localisation). The AUC were nearly the same (97%). The use of one sensor limits the number of cow variables that can be accurately detected by the monitoring system. Although some studies (Mattachini, Riva, Bisaglia, Pompe, & Provolo, 2013; Resheff, Rotics, Harel, Spiegel, & Nathan, 2014) suggest that one accelerometer could detect several cow variables, not all variables are detected with the same accuracy. As presented in Benaissa *et al.* (2017), neck-mounted accelerometer is better for monitoring ruminating and feeding behaviours, while leg-mounted accelerometer is better for lying behaviour monitoring (e.g. lying time, bouts). On the other hand, not all variables changed during oestrus. For example, the lying bouts and the time in feeding zone did not change significantly during the oestrus period. With all three sensors combined, the precision increased to 93% and the sensitivity increased to 90%. The use of different sensors increases the number of cow variables that could change during oestrus. These results show clearly an improved performance, enhancing the number of successful alerts and significantly reducing the number of false alarms.

Table 2. The precision (Pr), sensitivity (Se), specificity (Sp), overall accuracy, and AUC using one sensor, a combination of two sensors, and a combination of the three sensors

Model based on	Pr [%]	Se [%]	Sp [%]	Accuracy [%]	AUC [%]
Neck Acc	91±1.8	77±1.1	93±0.3	95±0.2	93±0.6
Leg Acc	92±2.4	77±1.2	92±0.5	95±0.3	94±0.4
Localisation	89±2.0	75±0.7	92±0.6	94±0.5	93±0.4
Neck + Leg Acc	89±2.9	78±0.7	98±0.6	95±0.5	93±0.6
Neck Acc + Localisation	86±3.2	88±1.9	97±0.5	97±0.8	97±0.5
Leg Acc+ Localisation	88±1.3	79±2.4	98±0.2	96±0.4	96±0.7
All sensors	93±1.4	90±1.3	99±0.2	98±0.3	99±0.1

Conclusions

In the present study, the combination of accelerometers (neck- and leg-mounted) and a localisation sensor was investigated for the detection of oestrus in dairy cattle. The performance at detecting oestrus was similar for each sensor separately (Se = 75-78%, AUC = 93-94%). The performance (and the sensitivity in particular) increased when localisation was combined with either a neck- or a leg-mounted accelerometer, especially for the sensitivity (AUC = 97%). The best performance was obtained with the combination of all three sensors (Se = 90%, AUC = 99%). This study demonstrates the potential of combining different sensors to increase the detection performance of oestrus monitoring systems for dairy cattle. Future work will consist of expanding this research to other herds with larger sample size as well as considering cows' anomalies (e.g. mastitis, lameness) and other sensors (e.g. bolus or eartag to measure the temperature).

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References

Arlot, S., & Celisse, A. (2010). A survey of cross-validation procedures for model selection. *Statistics Surveys*, 4, 40–79. http://doi.org/10.1214/09-SS054.

Benaissa, S., Tuyttens, F.A.M., Plets, D., Cattrysse, H., Martens, L., Vandaele, L., Sonck, B. (2018). Classification of ingestive-related cow behaviours using RumiWatch halter and neck-mounted accelerometers. *Applied Animal Behaviour Science*, (November), 1–8. http://doi.org/10.1016/j.applanim.2018.12.003.

Benaissa, S., Tuyttens, F.A.M., Plets, D., de Pessemier, T., Trogh, J., Tanghe, E., Sonck, B. (2017). On the use of on-cow accelerometers for the classification of behaviours in dairy barns. *Research in Veterinary Science*. http://doi.org/10.1016/j.rvsc.2017.10.005.

Borchers, M.R., Chang, Y.M., Proudfoot, K.L., Wadsworth, B.A., Stone, A.E., & Bewley, J.M. (2017). Machine-learning-based calving prediction from activity, lying, and ruminating behaviors in dairy cattle. *Journal of Dairy Science*, *100*(7): 5664–5674. http://doi.org/10.3168/jds.2016–11526.

De Silva, A.W.M.V., Anderson, G.W., Gwazdauskas, F.C., McGilliard, M.L., & Lineweaver, J.A. (1981). Interrelationships With Estrous Behavior and Conception in Dairy Cattle. *Journal of Dairy Science*. http://doi.org/10.3168/jds.S0022-0302(81)82864-0.

De Vries, A. (2010). Economic Value of Pregnancy in Dairy Cattle. *Journal of Dairy Science*. http://doi.org/10.3168/jds.s0022-0302(06)72430-4.

Dolecheck, K.A., Silvia, W.J., Heersche, G., Chang, Y.M., Ray, D.L., Stone, A.E., Bewley, J.M. (2015). Behavioral and physiological changes around estrus events identified using multiple automated monitoring technologies. *Journal of Dairy Science*. http://doi.org/10.3168/jds.2015–9645.

Gomez, A., & Cook, N.B. (2010). Time budgets of lactating dairy cattle in commercial freestall herds. *Journal of Dairy Science*. http://doi.org/10.3168/jds.2010–3436.

Groenendaal, H., Galligan, D.T., & Mulder, H.A. (2010). An Economic Spreadsheet Model to Determine Optimal Breeding and Replacement Decisions for Dairy Cattle. *Journal of Dairy Science*. http://doi.org/10.3168/jds.s0022-0302(04)70034-x.

Homer, E.M., Gao, Y., Meng, X., Dodson, A., Webb, R., & Garnsworthy, P.C. (2013). Technical note: A novel approach to the detection of estrus in dairy cows using ultra-wideband technology. *Journal of Dairy Science*. http://doi.org/10.3168/jds.2013–6747.

Ito, K., Weary, D.M., & von Keyserlingk, M.A.G. (2009). Lying behavior: Assessing within- and between-herd variation in free-stall-housed dairy cows. *Journal of Dairy Science*. http://doi.org/10.3168/jds.2009–2235.

Jónsson, R., Blanke, M., Poulsen, N.K., Caponetti, F., & Højsgaard, S. (2011). Oestrus detection in dairy cows from activity and lying data using on-line individual models. *Computers and Electronics in Agriculture*. http://doi.org/10.1016/j.compag.2010.12.014.

Mattachini, G., Riva, E., Bisaglia, C., Pompe, J.C.A.M., & Provolo, G. (2013). Methodology for quantifying the behavioral activity of dairy cows in freestall barns. *Journal of Animal Science*, *91*(10): 4899–4907. http://doi.org/10.2527/jas2012–5554.

Meadows, C., Rajala-Schultz, P.J., & Frazer, G.S. (2010). A Spreadsheet-Based Model Demonstrating the Nonuniform Economic Effects of Varying Reproductive Performance in Ohio Dairy Herds. *Journal of Dairy Science*. http://doi.org/10.3168/jds.s0022-0302(05)72791-0.

Pahl, C., Hartung, E., Mahlkow-Nerge, K., & Haeussermann, a. (2015a). Feeding characteristics and rumination time of dairy cows around estrus. *Journal of Dairy Science*, *98*(1): 148–154. http://doi.org/10.3168/jds.2014–8025.

Pahl, C., Hartung, E., Mahlkow-Nerge, K., & Haeussermann, A. (2015b). Feeding characteristics and rumination time of dairy cows around estrus. *Journal of Dairy Science*. http://doi.org/10.3168/jds.2014–8025.

Porto, S.M.C., Arcidiacono, C., Giummarra, A., Anguzza, U., & Cascone, G. (2014). Localisation and identification performances of a real-time location system based on ultra wide band technology for monitoring and tracking dairy cow behaviour in a semi-open free-stall barn. *Computers and Electronics in Agriculture*. http://doi.org/10.1016/j.compag.2014.08.001.

Reith, S., Brandt, H., & Hoy, S. (2014). Simultaneous analysis of activity and rumination time, based on collar-mounted sensor technology, of dairy cows over the peri-estrus period. *Livestock Science*, *170*, 219–227. http://doi.org/10.1016/j.livsci.2014.10.013.

Reith, S., & Hoy, S. (2012). Relationship between daily rumination time and estrus of dairy cows. *Journal of Dairy Science*. http://doi.org/10.3168/jds.2012–5316.

Reith, S., & Hoy, S. (2018). Review: Behavioral signs of estrus and the potential of fully automated systems for detection of estrus in dairy cattle. *Animal*. http://doi.org/10.1017/S1751731117001975.

Resheff, Y.S., Rotics, S., Harel, R., Spiegel, O., & Nathan, R. (2014). AcceleRater: a web application for supervised learning of behavioral modes from acceleration measurements. *Movement Ecology*, *2*, 27. http://doi.org/10.1186/s40462-014-0027–0.

Roelofs, J., López-Gatius, F., Hunter, R.H.F., van Eerdenburg, F.J.C.M., & Hanzen, C. (2010). When is a cow in estrus? Clinical and practical aspects. *Theriogenology*. http://doi.org/10.1016/j.*Theriogenology*.2010.02.016.

Rutten, C.J., Kamphuis, C., Hogeveen, H., Huijps, K., Nielen, M., & Steeneveld, W. (2017). Sensor data on cow activity, rumination, and ear temperature improve prediction of the start of calving in dairy cows. *Computers and Electronics in Agriculture*. http://doi.org/10.1016/j.compag.2016.11.009.

Sperandei, S. (2014). Understanding logistic regression analysis. *Biochemia Medica*. http://doi.org/10.11613/BM.2014.003.

Stevenson, J.S. (2001). A review of oestrous behaviour and detection in dairy cows. *BSAP Occasional Publication*, 26, 43–62. http://doi.org/10.1017/s0263967x00033589.

Tullo, E., Fontana, I., Gottardo, D., Sloth, K.H., & Guarino, M. (2016). Technical note: Validation of a commercial system for the continuous and automated monitoring of dairy cow activity. *Journal of Dairy Science*. http://doi.org/10.3168/jds.2016–11014.

Goats monitoring at the pasture scale combining convolutional neural network and time-lapse cameras

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Abstract

This paper presents a system for animal monitoring on pasture that combines a state-of-the-art object detection algorithm named YOLO, and low cost time-lapse cameras. The cameras network takes pictures of the flock every 30 seconds. The pictures are then analysed by several algorithms in order to automatically detect the animals and estimate their positions on the pasture. The system was tested on a 1,300 m^2 pasture with 18 creole goats and 22 kids. Based on 1,000 pictures selected randomly, the animal detection sensitivity was estimated to 81.3% and the precision to 97.1%. Unlike GPS, where one sensor per animal is needed, the system can be used to provide quantitative information on the entire flock using only three passive sensors. We used it to study the flock during two grazing weeks on the same pasture, with one month interval. We showed that from one week to another, the flock spatial distribution was highly correlated. The correlation is not constant but decreases gradually during the week, probably due to a decrease of the most appetizing resources. More generally, the flock successive positions can be used for quantitative studies on animal behaviour, animal health and welfare, or to improve pasture management.

Keywords: animal monitoring, image analysis, animal activity, animal position

Introduction

Automatic acquisition of information on animals is of interest in several fields and already has a long history. Most examples can be found in ecology as in determining animal home range (Millspaugh and Marzluff, 2001), or describing animal social behaviour (Crawley *et al.*,). Some can be seen in agriculture as well (Fogarty *et al.,* 2018), such as studying animal foraging behaviour (Baumont *et al.,* 2000) or quantifying animal physiological status (Nilsson *et al.,* 2015). The nature of the information that can be gathered is as large as the number of applications as, for example, animal weight (Jun, Kim, and Ji 2018) or urination events (Lush *et al.,* 2018). In this study, we will focus on monitoring spatial location of animals. Monitoring displacement of animals can be particularly useful to determine health status and animal welfare (Oczak *et al.,* 2016). It can also help to improve pasture management by better understanding pasture uses (Putfarken *et al.,* 2008) or can help understanding host-parasite interactions (Bonneau *et al.,* 2018). The most common technique for monitoring spatial location remains using GPS collar (Fogarty *et al.,* 2018). A major drawback of on-animal sensors is that a device has to be attached on each animal, which limits the number of studied animals for cost reasons but also requires batteries to be reloaded regularly. Another constraint is the quality of GPS signal that can be randomly low or decreases because of the environment or time of the day. An alternative approach consists of using one sensor that will monitor the entire group of animals, such as a camera (Benvenutti *et al.,* 2015). In this case, videos or pictures of the flock are stored and an automatic detection procedure can be used to detect animals on the pictures and estimate their positions. A major constraint in this case is camera field of view, which can be too limited to cover a large study area, although satellite imagery can be used (Fretwell,

2014). Nonetheless, in agriculture, many studies are conducted at the field or shelter scale and a small network of common cameras can be sufficient. Finally, automatic animal detection remains a difficult problem but recent developments in computer vision offer promising solutions (Hollings *et al.,* 2018). In this study, we proposed to combine a state-of-the-art object detection algorithm named YOLO (Redmon *et al.,* 2016) to a network of time-lapse cameras in order to monitor a flock of 40 individuals.

Material and methods

Study site

The study took place at the INRA-PTEA farm located in Guadeloupe, French West Indies. The farm is mostly breeding creole goats and we selected a flock of 18 goats and 22 kids that are managed under rotational grazing. The flock is grazing successively on five different pastures, spending one week per pasture. We monitored the flock during a first week from 28 December 2018–3 January 2019 and one month later when the flock was back on the same pasture, from 1 February to 7 February 2019. The pasture was approximately 1,300 m^2 and was selected for its regular rectangular shape (see Figure 1).

Time-lapse cameras network

We used three Brinno TLC200 Pro time-lapse cameras to take pictures of the flock every 30 seconds, from 6 am to 6 pm. The cameras are distributed on one side of the pasture, spaced 21 meters from each other. The pasture was virtually divided into three different zones of 427 m^2, 418 m^2 and 490 m^2, and one camera was allocated to each zone. Cameras were fixed on permanent steel posts at approximately 1 m 70 height, and kept the same positions during the experiment. See Figure 1 for a schematic representation of the monitoring system.

Objects detection

We used the convolutional neural network named YOLO (You Only Look Once) to detect objects on the image. YOLO was compared on different Pascal VOC image data sets and was shown to provide good precision while allowing real-time object detection. The algorithm is freely available and implemented in Python. For each picture, the algorithm output is a set of Bounding Boxes (bbox) around the detected objects.

Merging overlapping bounding boxes

In general, several parts of an object are detected. As a consequence, multiple bbox might correspond to the same objects and in some cases, a bbox can also contain several objects. We proposed to use a simple technique consisting of finding and merging all the overlapping bbox. In this case, the top left corner of the final bbox is equal to the maximum top left corner of all the overlapping bbox.

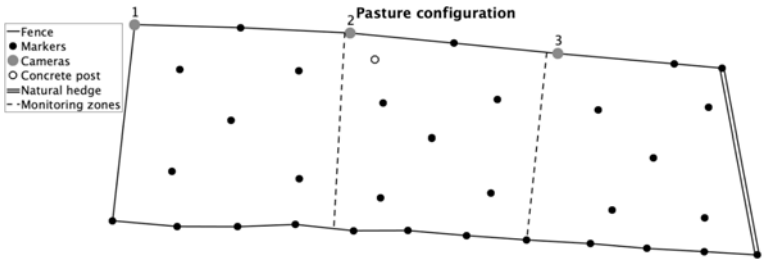

Figure 1. Pasture schematic representation. Pasture proportions and relative distances between elements are respected

The bottom right corner of the final bbox is equal to the maximum bottom right corners of the overlapping bbox. Unfortunately in some cases, bbox of several individuals are merged into one bbox. To quantify the frequency at which the bbox contained multiple individuals, we selected randomly 1,000 bbox after the merging process and counted the number of times multiple individuals were present. We found that in 19.6% of the cases, multiple individuals were present. See Figure 2 for illustrative examples.

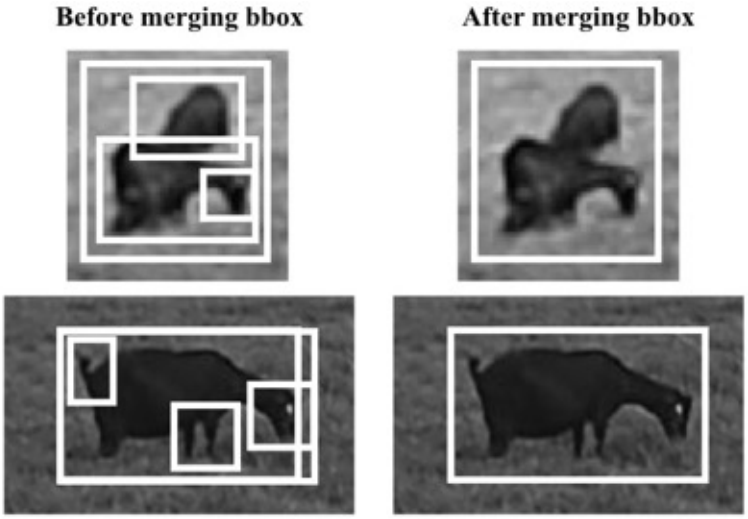

Figure 2. The Bounding Boxes (bbox) merging problem. On the left are two examples of the YOLO algorithm outputs. The bbox are in white and we can see that several bbox are linked to the same individual. On the top pictures, there is one bbox surrounding two individuals, which results in multiple individuals in the same bbox after the merging process (top right picture). When the animal is isolated from others, the merging process results in only one bbox per individual (bottom right picture)

Image registration

At this stage, all the objects on the pictures are theoretically detected and it is now necessary to estimate their positions on the pasture.

We deployed a set of markers that can easily be seen on the camera pictures. We used steel posts knocked approximately 30 cm above the ground. The top of each post was painted in red to help detection. We also deployed some plastic red markers on the fence around the pasture. In total, 30 markers were used and kept at the same positions during the experiment. For each marker, we measured distances with at least three other markers, and used a triangulation technique to compute their spatial coordinates. The coordinates of the pasture top left corner, where the first camera is located, was fixed to . Finally, for each camera, the pixel coordinates of the visible markers and their spatial coordinates were used to fit a projective geometric transformation (Goshtasby, 1988).

Removing false positive detections

After a first visual analysis of the results, we mainly observed three types of false positive detections: (i) some birds that are naturally present on the pasture, (ii) some of the fence parts and (iii) grass tussocks. To remove these false positive detections, we trained an image category classifier using a bag of visual words (Csurka *et al.*, 2004). The detected objects of type (ii) and (iii) were generally detected on most of the pictures and it was thus

easy to determine the positions of these objects using a spatial occurrence frequency analysis. To construct the training data set for the image category classifier, we randomly selected bbox inside the high frequency zones and classified them manually. Finally, type (i) detected objects were not located on a specific location, but represent an important proportion of the detected objects. We selected randomly some of the detected bbox until 100 bird pictures were found. One classifier was trained per camera and approximately 650 pictures were used to train each classifier.

Results

Removing false positives detections

For each camera, the dataset was separated into a training dataset containing 60% of the pictures and a test dataset containing 40% of the pictures. The confusion matrix for each classifier is available in Table 1. On the entire experiment, approximately 31% of the detected bbox were removed by the classifier.

Table 1. Confusion matrix for each category classifier of the cameras

		Prediction cam1		**Prediction cam 2**		**Prediction cam3**	
		Goat	**Not Goat**	**Goat**	**Not Goat**	**Goat**	**Not Goat**
True	Goat	0.89	0.11	0.97	0.03	0.92	0.08
	Not Goat	0.14	0.86	0.13	0.87	0.08	0.92

Method efficacy

We randomly selected 100 pictures of the time-lapse cameras and manually counted the number of true positives, false positives and false negatives detections. We then computed the sensitivity and precision of the method, respectively defined as:

$$\frac{true\ positives}{true\ positives + false\ negatives} \quad and \quad \frac{true\ positives}{true\ positives + false\ positives}$$

We found a sensitivity of 81.3% and a precision of 97.1%. The false negatives detections were mostly located in two different zones. The first zone is in front of the second camera, where a concrete post of approximately 1 m 20 height is installed (see Figure 1). The classifier was trained to delete the bbox containing the post and thus, all the animals around the post are generally deleted. The second zone, monitored by the third camera, is located at the end of the pasture where a natural hedge is present. The hedge appeared black on the camera pictures and the animal in front of it was very hard to distinguish. If the method efficacy is computed on all the pastures but these two zones, the precision is unchanged but the sensitivity is increased at 89%. Also, note that young kids can be hard to detect due to their small size. Finally, some false negatives detection might be caused by the category classifier. As shown in Table 1, the first classifier removed 11% of the bbox mistakenly.

Application

We used our framework to compare pasture uses between each grazing week. We virtually divided the pasture into quadrats of 3 m by 3 m and computed the average quadrats occupancies, more precisely the number of animals detected on the quadrat, divided by the number of pictures. We computed the cumulated occupancy for each week and each day of the experiment. Visually, pasture occupancy distribution is very similar between the two weeks. We found a Pearson's correlation coefficient between the quadrats occupancies

over the first and second week equals to 0.74. We also computed the quadrats occupancies on each grazing day. We found a Pearson's correlation coefficient equals to 0.61 between the first and second grazing week, and equals to 0.65, 0.6, 0.57, 0.45, 0.29, 0.16 for the next six days. This certainly shows that the most appetising quadrats are grazed during the first days on the pasture and that grazing is more diverse at the end of the grazing period.

Discussion

Similar studies using image analysis to detect farmed animals are generally conducted in indoor environments with top view cameras. This problem configuration allows background subtraction techniques to be used, which generally exhibit better sensitivity values. Our case study is more complicated because the background is constantly moving due to light variations and to grass movement with wind. Also, because other objects can appear on the pictures (e.g. birds) and the contrast and luminosity are variable inside the pasture (e.g. shade or dark background). Nonetheless, our method provides encouraging results and a high precision value, meaning that detected bbox can be trusted. Our method still has to be improved, in particular for merging the bbox from YOLO. For example, each bbox can be reanalysed by YOLO in order to detect if multiple animals are present. To decrease the number of false negatives observations, more cameras can be used, for example, near the hedge at the end of the pasture. Reducing the number of objects on the pasture (e.g. the concrete post) can also help to reduce the number of false positives detections.

Conclusion

We have designed a system allowing a flock of small ruminants to be monitored, for a relatively low cost. The system offers interesting perspectives in terms of grazing behaviour, pasture management studies, or for animal health and welfare.

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References

Baumont, R, S Prache, M Meuret, and P Morand-Fehr. (2000). How Forage Characteristics Influence Behaviour and Intake in Small Ruminants: A Review. *Livestock Production Science,* 64(1). Elsevier: 15–28.

Benvenutti, MA, TW Coates, A Imaz, TK Flesch, J Hill, E Charmley, Graham Hepworth, and D Chen. (2015). The Use of Image Analysis to Determine the Number and Position of Cattle at a Water Point. *Computers and Electronics in Agriculture* 118. Elsevier, 24–27.

Bonneau, M., Bambou, JC., Mandonnet, N. Arquet, R. and Mahieu, M. (2018). Goats Worm Burden Variability Also Results from Non-Homogeneous Larval Intake. *Scientific Reports* 8 (1). Nature Publishing Group: 15987.

Crawley, J.N., S. Szara, G.T. Pryor, C.R. Creveling, and B.K. Bernard. (1982). Development and Evaluation of a Computer-Automated Color Tv Tracking System for Automatic Recording of the Social and Exploratory Behavior of Small Animals. *Journal of Neuroscience Methods*, 5(3): 235–47.

Csurka, G., Dance, C., Fan, L., Willamowski, J., & Bray, C. (2004). Visual categorization with bags of keypoints. In *Workshop on statistical learning in computer vision, ECCV* (Vol. 1, No. 1-22, pp. 1-2).

Fogarty, E.S., Swain, D.L., Cronin, G. and Trotter, M. (2018). Autonomous on-Animal Sensors in Sheep Research: A Systematic Review. *Computers and Electronics in Agriculture,* 150: 245–56.

Fretwell, I.J., and Forcada, P.T. and Staniland. (2014). Whales from Space: Counting Southern Right Whales by Satellite. *PLOS ONE* 9 (2). Public Library of Science, 1–9.

Goshtasby, Ardeshir. (1988). Image Registration by Local Approximation Methods. *Image and Vision Computing,* 6(4). Elsevier, 255–61.

Hollings, T., Burgman, M., Van Andel, M., Gilbert, M., Robinson, T., and Robinson, A. (2018). How Do You Find the Green Sheep? A Critical Review of the Use of Remotely Sensed Imagery to Detect and Count Animals. *Methods in Ecology and Evolution* 9 (4). Wiley Online Library, 881–92.

Jun, Kyungkoo, Si Jung Kim, and Hyun Wook Ji. (2018). Estimating Pig Weights from Images Without Constraint on Posture and Illumination. *Computers and Electronics in Agriculture,* 153: 169–76.

Lush, L., Rory P.W., Mark D.H., Hopkins, P., Marsden, K.A., Chadwick, D.R., and King, A.J. (2018). Classification of Sheep Urination Events Using Accelerometers to Aid Improved Measurements of Livestock Contributions to Nitrous Oxide Emissions. *Computers and Electronics in Agriculture* 150: 170–77.

Millspaugh, J.J., and Marzluff, J.M. (2001). Chapter 15 - Radio-Tracking and Animal Populations: Past Trends and Future Needs. In *Radio Tracking and Animal Populations*, edited by Joshua J. Millspaugh and John M. Marzluff, 383–93. San Diego: Academic Press.

Nilsson, M., Herlin, A.H., Ardö, H., Guzhva, O., Åström, K., & Bergsten, C. (2015). Development of automatic surveillance of animal behaviour and welfare using image analysis and machine learned segmentation technique. *Animal*, *9*(11) : 1859–1865.

Oczak, M., Maschat, K., Berckmans, D., Vranken, E., and Baumgartner, J. (2016). Can an Automated Labelling Method Based on Accelerometer Data Replace a Human Labeller? – Postural Profile of Farrowing Sows. *Computers and Electronics in Agriculture,* 127: 168–75.

Putfarken, D., Dengler, J., Lehmann, S., and Härdtle, W. (2008). Site Use of Grazing Cattle and Sheep in a Large-Scale Pasture Landscape: A Gps/Gis Assessment. *Applied Animal Behaviour Science,* 111(1): 54–67.

Redmon, J., Divvala, S. Girshick, R. and Farhadi, A. (2016). You Only Look Once: Unified, Real-Time Object Detection. In *Proceedings of the Ieee Conference on Computer Vision and Pattern Recognition*, 779–88.

Monitoring feeding behaviour of dairy cows using UHF-RFID

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Abstract

Feeding behaviour in terms of duration and daily pattern contains valuable information about the metabolic health of dairy cows. Several commercial systems are available to measure this behaviour. However, since these sensors can be expensive, it would be beneficial to develop a simple and cost effective system for this purpose. Thus, the objectives of this study were: 1) to optimise the setup of a UHF-RFID system for monitoring feeding behaviour at the feeding fence by passive UHF ear tags and 2) to characterise the size and shape of the reading area of the system testing two different antenna positions relative to the feeding fence and two types of UHF ear tags. A free-form UHF cable antenna with 6 m active length was placed along a section of the feeding fence in a conventional free-stall barn using pipe clamps. The two antenna arrangements were compared by manually measuring the reading range in a grid with four measurement heights in front of and behind the feeding fence. The measurements revealed that a greater distance of the antenna to the wall resulted in a higher reading range. However, the reading range decreased along the antenna. The antenna position closer to the feeding fence in combination with ear tag Type B showed promising results. Thus, it was chosen for further tests. In a next step, the system will be extended along the feeding fence and validated with cows using video observations.

Keywords: ultra-high frequency radio frequency identification, feed fence, feeding time, validation, indoor positioning

Introduction

Feeding behaviour is among the most important behaviours and can be used as an indicator of animal health and welfare. Changes in feeding behaviour are not only caused by changes in feed or management, but especially by diseases or welfare impairments (Weary *et al.,* 2009). To detect changes in behaviour reliably, automated technical systems are needed, that are able to record feeding behaviour. The most precise way to measure not only feeding time, duration and daily pattern is the use of feed bunk weighing systems with electronic identification of single animals (e.g. Chapinal *et al.,* 2007). These systems are widely used in research, but are too expensive for use on commercial farms. Another way to record feeding and also rumination behaviour are sensor systems that either detect the jaw movements of the cow directly (Zehner *et al.,* 2017) or indirectly by measuring the movement of the head or neck (Grinter *et al.,* 2019) or ear (Reiter *et al.,* 2018). However, these systems are also expensive and demand a power supply on the sensor. A possible solution for developing a cost effective feeding behaviour monitoring system could be radio-frequency identification (RFID) systems. Recently, researchers have applied especially ultra-high frequency (UHF) RFID technology for measuring different behaviours of pigs (Adrion *et al.,* 2018), poultry (e.g. Li *et al.,* 2017) and cattle (Toaff-Rosenstein *et al.,* 2017). The advantages of this technology are a flexible and high reading range up to several meters, the ability to detect many animals simultaneously and the use of passive transponders, which do not require a battery.

The objectives of this study were: 1) to optimise the setup of a UHF-RFID system for monitoring feeding behaviour at the feeding fence by passive UHF ear tags and 2) to

characterise the size and shape of the reading area of the system testing two different antenna positions and two types of UHF ear tags. The overall aim was to optimise the system by finding a setup that allowed for reliable identification of ear tags in front of the feeding fence with no detections behind the fence, if possible.

Material and methods

Experimental barn and technical equipment

The measurements were carried out in an experimental dairy barn for comparative emission measurements at BBZ Arenenberg in Tänikon) (Switzerland) described in Schrade *et al.* (2016). The barn is devided into two compartments for 20 cows each.

At the feeding fence of the western barn compartment, a free-form UHF cable antenna (Locfield® Antenna, Cavea Identification GmbH, Olching, Germany) was mounted. This type of antenna was chosen because of the possibility to cover a relatively long part of the feeding fence with only one antenna. The antenna had an active length of 6 m and a passive length of 1 m including the damping unit. It was made of a coaxial cable with 5 mm diameter and an attenuation of approx. 0.29 dB/m. The antenna was connected to the UHF reader with a coaxial cable of 5 m length damping 0.27 dB/m ('H-155 PE', Belden Wire & Cable B.V., Venlo, Netherlands). In total, this resulted in a loss of approx. 3.5 dB from the reader to the tip of the antenna, where the antenna field originates.

The reader used was an Impinj Speedway Revolution R420 model for the ETSI frequency range (Impinj Inc., Seattle, WA, USA). The output power of the reader was 31.5 dBm during the tests, resulting in an effective output power of approx. 28 dBm at the tip of the cable antenna. The receiver sensitivity was set to the maximum value of 70 dBm and the reader could flexibly switch between channels 4, 7, 10 and 13 (865.7, 866.3, 866.9 and 867.5 MHz). Additionally, the reader was operated in 'dense reader mode (M = 8)' to enhance the robustness against other activity within the UHF-RFID frequency range.

The tests were conducted with two different types of UHF transponder ear tags, which were both functional models and were not commercially available. Type A contained a transponder with a planar inverted F-shaped (PIF) antenna approx. 50 × 50 mm in size (deister electronic GmbH, Barsinghausen, Germany). It was combined with an Impinj Monza® 4D chip (Impinj Inc., Seattle, WA, USA) and integrated into a Primaflex® cattle ear tag (Caisley International GmbH, Bocholt, Germany) by injection molding (Figure 1). Type B was a functional model provided by Scot EID Livestock Traceability Research (Huntly, United Kingdom). It contained an Alien Garment Tag (GT) ('ALN-9728', Alien Technology LLC, San José, CA, USA) with a dipole antenna and an Alien Higgs® 4 chip. This tag was 50 × 30 mm in size. It was encapsulated in an air-filled pocket molded onto a regular two-piece ear tag for cattle.

Experimental Setup

Since the way of mounting and the proximity to surrounding materials strongly influence the antenna field and the reading performance of UHF flex-form cable antennae, the experimental setup is subsequently described in detail.

Two different mounting positions of the antenna were tested (Figure 2). Since pre-tests showed that the antenna field was weakened severely in proximity to reinforced concrete or metal, the antenna was mounted with a distance to the feeding fence and the wall below the fence. For this purpose, six pairs of pipe clamps (diameter 2 inch at the fence, 1 inch at the antenna) were connected to the feeding fence ('Comfort Flexi', Krieger AG, Lenggenwil SG, Switzerland) and coupled with a metal pipe (diameter 0.5 inch). The first pair of clamps was mounted at a distance of 26 cm to the side wall of the barn compartment. The other

clamps followed along the feeding fence at distances of 179, 157, 161, 150 and 68 cm to fit in between the feeding places. The 1" clamps were filled with a rubber foam to hold a flexible PVC pipe ('PLICA UV-FLEX M25', Plica AG, Frauenfeld, Switzerland). The antenna was inserted into the flexible PVC pipe, so that it was mechanically protected.

Figure 1. Left: UHF ear tag Type A, right: UHF ear tag Type B

Figure 2. Setup of the antenna at the feeding fence, left: Antenna Position 1, middle: Antenna Position 2, right: ear tag holder (polystyrene foam) with supporting pipes of different lengths to maintain the measurement heights

The wall below the feeding fence was 14 cm wide. The top of the wall was 33 cm above the feeding alley and 48 cm above the walking alley behind the feeding fence. In Position 1, the antenna was mounted in a horizontal distance of 18 cm to the center of the wall and 24 cm above the concrete floor of the feeding alley. In Position 2, the horizontal distance to the wall was reduced to 14 cm and the height above the floor was increased to 32 cm. This antenna position was chosen because it would interfere with the movement of the cows during feeding much less than Position 1. The length of the distance pieces between the two pipe clamps of each pair was 16 cm and 8 cm for Positions 1 and 2, respectively. The tip of the cable antenna was placed 63 cm apart from the side wall of the barn compartment. In this way, the antenna covered eight feeding places. Its active length ended 30 cm behind feeding place no. 8. The first feeding place of the fence was at a distance of 83 cm apart from the side wall. The further places followed in an interval of 78.5 cm. The moveable parts of the feeding places were set to 'closed' position for the experiment.

Measurement procedure and test design

A coordinate grid was established to measure the reading range of the antenna in front of and behind the feeding fence. In the middle of each of the first nine feeding places measurement points were marked close to the feeding wall on both sides (+14 cm (front) and -16 cm (back) from the centre of the wall) and in greater distances (+32, +57, 32, 57 and 82 cm). The coordinates in front of the feeding fence represented the middle and end of the floor coating, where the feed is normally provided to the cows. At the backside of the feeding fence, the measurement points at 82 cm were added to detect unwanted readings in this area. Pre-tests showed that beyond this point no ear tags could be detected in both antenna positions. The coordinates were repeated in four different heights above the floor on both sides of the feeding fence (30, 55, 80 and 105 cm). The bottom of the tags was positioned in these heights for the measurements.

Therefore, an ear tag holder was constructed out of polystyrene foam to ensure that all measurements were performed identically, at the correct height, and with as little as possible influence of the measuring person on the tags. Polystyrene foam has very little influence on the electromagnetic fields of the reader and tag (relative permittivity $\varepsilon_r = 1.03$) and is used as a standard mounting material in high-frequency tests. The tags were inserted in a vertical position into a notch in the material. A hole was drilled into the bottom of the holder to be able to put it on top of PVC pipes. Four PVC pipes with a diameter of 5 cm were cut in different lengths to hold the tags in the targeted heights above the floor. The distance between the top of the pipes and the bottom of the tag in the holder was 4 cm. For the measurements, the holder with the ear tag was positioned at a coordinate and then turned around 360 degrees horizontally. If at least one successful reading of the tag took place during this turn, the tag was labelled as 'detected' at this coordinate.

Three samples of each of the two types of UHF ear tags were randomly chosen for the experiment. Out of these samples, three pairs with one tag of each type were combined randomly and the measurement order within these pairs was also randomly chosen. The pairs were measured one after each other in a random order. First, all measurements with Antenna Position 1 were conducted. All measurements of each UHF ear tag were performed at once before measuring the next tag. The order of the measurements was the following: starting at the closest coordinate to the feeding wall at the front of the feed fence (+ 14 cm), first, the distance to the wall was increased by proceeding to the next coordinates (+32 cm, +57 cm). This was done for each of the nine feeding places one after each other. After finishing all measurements at one height, the measurements at the next height level were conducted identically. After measuring at the coordinates at the front of the feeding fence, the same procedure was conducted at the coordinates at the back of the feeding fence. The same procedure was followed with Antenna Position 2 with the same, but newly randomized ear tags. It has to be noted, that at a height of 30 cm no measurements could be made directly in front of the feeding fence (+14 cm), because the antenna was blocking this position in both treatments.

Data analysis

For the analysis, the percentage of successful detections for each coordinate was calculated per type of tag and antenna position over all heights. At maximum, 12 detections were achievable during the measurements of three tags in four heights (only three heights at the coordinate +14 cm), which would be a detection rate of 100%. With these data, contour plots were created using Sigmaplot 13 (Systat Software Inc., San José, CA, USA). In addition, contour plots for each type of tag and antenna position were created for each measurement height separately. Further, the number of coordinates with at least one successful detection in front of and behind the feeding fence was calculated for each antenna position and type of ear tag.

Results and discussion

The visualisation of the measurements showed that the reading area differed strongly between both antenna positions and also both types of UHF ear tag (Figure 3 and Figure 4). Note that a detection rate of e.g. 25% means that this type of ear tag was detected at least three times at a certain coordinate. Thus, the visualisations in Figures 3 and 4 tend to underestimate the reliability of reading. It would be sufficient to read tags successfully at one or two measurement heights to detect the cows' presence at the feed trough. Close to the floor most readings should take place when the cows are feeding. This indeed fits well to the results collected with both antenna positions in this experiment.

However, in all treatments, the reading area was not evenly shaped, but showed irregular gaps. In addition, areas with a higher reading range were also detected. Furthermore, a strong decrease of the reading range was visible over the length of the antenna, beginning with a high detection rate and greater reading area at the tip of the antenna. In general, with Antenna Position 1 the reading area was larger than with Position 2. For tag Type B a larger reading area could be measured with both antenna positions compared to tag Type A. Accordingly, with tag Type A reliable detection (> 25% detection rate) was only possible at six feeding places in a row in both antenna positions. Tag Type B was reliably detectable at nine (Antenna Position 1) and seven feeding places in a row (Antenna Position 2).

The differences between the antenna positions and the types of UHF ear tag were also evident in the number of coordinates, at which at least one successful detection of a tag was registered over all measurement heights. Tag Type B was detected only at nine coordinates behind the feeding fence with Antenna Position 2 compared to 18 coordinates with Antenna Position 1. Interestingly, for tag Type A, a slight increase from two to five detections behind the feeding fence was registered in Antenna Position 2.

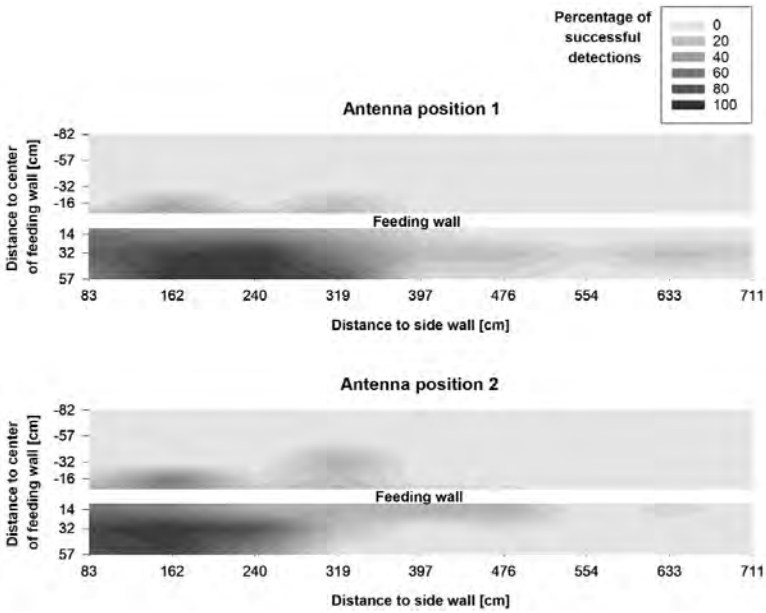

Figure 3. Interpolated contour plot showing the percentage of successful detections per coordinate of UHF ear tag Type A over all heights and for both antenna positions. Major ticks on the x- and y- axes indicate the measurement coordinates

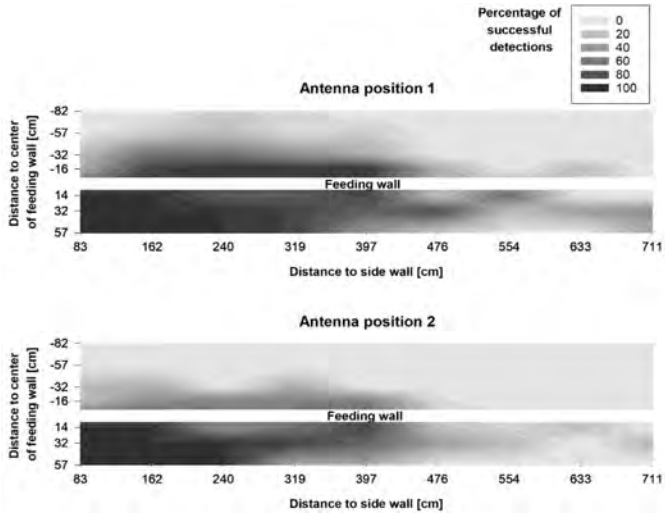

Figure 4. Interpolated contour plot showing the percentage of successful detections per coordinate of UHF ear tag Type B over all heights and for both antenna positions. Major ticks on the x- and y-axes indicate the measurement coordinates

As mentioned above, for the detection of cows' feeding visits it would be sufficient to detect the ear tags in a height of 30–55 cm. The treatment, which fullfilled this requirement best, was Antenna Position 2 in combination with tag Type B. Furthermore, above 55 cm height, at only six coordinates 16 and 32 cm behind the feeding fence readings were registered in this variant, which is promising in terms of a low error rate.

The method applied for measuring the reading area in this experiment is rather simple compared to other methods of testing UHF-RFID systems (e.g. Derbek *et al.,* 2007; Adrion *et al.,* 2015) and also limited to this specific application environment in the experimental barn. Hoewever, the results were very consistent between all samples of each type of tag in both antenna positions. All things considered, this method seems to be a good compromise between the informative value of and effort for the measurements.

The results show the difficulty of generating an evenly shaped reading area with an UHF RFID system. Compared to low-frequency RFID systems, as presented, for example, by Brown-Brandl and Eigenberg (2011), UHF-RFID offers the possibility to use fewer antennas for the same number of feeding spaces, which could make such a system more cost-effective for commercial applications. Especially with the flex-form cable antennas used in this study long reading areas can be covered. However, antenna fields always have a circular or elliptical shape, so that it is easier to adapt several small antenna fields to a rectangular reading area (e.g. shown by Li *et al.,* 2017), than few large fields. The free-form cable antenna exhibits a decreasing diameter of the reading field along the antenna. Hence, some overlap of the antennas might be necessary to cover the whole length of the feeding fence. The manufacturer suggests to insert small U-turns near the end of the antenna to strenghten the field there. Unfortunately, with the need to protect the antenna mechanically, this was not possible in the current setup.

It was expected that no detections would be registered behind the feeding fence due to reflection of the antenna field on the metal of the fence. However, the opposite was the case. In particuclar, very close to the feeding wall, which is made out of reinforced conrete, many readings took place. A possible explanation is that due to the proximity

of the antenna to the wall, the antenna field coupled with the metal within the concrete wall, making the wall part of the antenna. This not only led to unwanted readings behind the feeding wall, but also was a major loss of energy that would have been useful for a stronger antenna field at the end of the antenna.

However, the results with Antenna Position 2 were promising for further tests. Especially with tag Type B up to 7 feeding spaces were reliably covered by the reading field while showing a reasonable amount of unwanted detections. It can be expected that the reading area will be smaller when the ear tags will be attached to the cows, because the ear tissue aborbs radiation from the reader and causes a shift of the tag resonance frequency (Adrion *et al.,* 2017). Even though this could impair the readings in front of the feeding fence, this could also reduce the number of unwanted readings behind the feeding fence.

Conclusions and outlook

The results of this experiment point out the challenges of setting up UHF antennae in a barn environment. With the free-form cable antenna used, the influence of metal in the surrounding area was evident. Thus, thorough testing of the system setup is necessary for every UHF RFID application. However, UHF RFID still offers greater flexibility for monitoring animal behaviour in various applications compared to other RFID frequencies. In the experiment conducted, an antenna setup in combination with a UHF ear tag could be found, which seems promising for detecting feeding visits of dairy cows. As a next step, the system will be extended along the feed fence using three cable antennae and validated with video observations as a gold standard. First results of the validation will be presented at the conference.

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References

Adrion, F., Hammer, N., Rößler, B., Jezierny, D., Kapun, A. & Gallmann, E. (2015). Development, function and test of a static test bench for UHF-RFID ear tags. *Landtechnik,* 70: 46–66.

Adrion, F., Kapun, A., Eckert, F., Holland, E.-M., Staiger, M., Götz, S. & Gallmann, E. (2018). Monitoring trough visits of growing-finishing pigs with UHF-RFID. *Computers and Electronics in Agriculture,* 144: 144–153.

Adrion, F., Kapun, A., Holland, E.-M., Staiger, M., Löb, P. & Gallmann, E. (2017). Novel approach to determine the influence of pig and cattle ears on the performance of passive UHF-RFID ear tags. *Computers and Electronics in Agriculture,* 140: 168–179.

Brown-Brandl, T.M. & Eigenberg, R.A. (2011). Development of a livestock feeding behavior monitoring system. *Transactions of the ASABE,* 54: 1913–1920.

Chapinal, N., Veira, D.M., Weary, D.M. & von Keyserlingk, M.A.G. (2007). Technical note: validation of a system for monitoring individual feeding and drinking behavior and intake in group-housed cattle. *Journal of Dairy Science,* 90: 5732–5736.

Derbek, V., Steger, C., Weiss, R., Preishuber-Pflügl, J. & Pistauer, M. (2007). A UHF RFID measurement and evaluation test system. *Elektrotechnik und Informationstechnik,* 124: 384–390.

Grinter, L.N., Campler, M.R. & Costa, J.H.C. (2019). Technical note: Validation of a behavior-monitoring collar's precision and accuracy to measure rumination, feeding, and resting time of lactating dairy cows. *Journal of Dairy Science* (in press).

Li, L., Zhao, Y., Oliveira, J., Verhoijsen, W., Liu, K. & Xin, H. (2017). A UHF RFID System for Studying

Individual Feeding and Nesting Behaviors of Group-Housed Laying Hens. *Transactions of the ASABE*, 60: 1337–1347.

Reiter, S., Sattlecker, G., Lidauer, L., Kickinger, F., Öhlschuster, M., Auer, W., Schweinzer, V., Klein-Jöbstl, D., Drillich, M. & Iwersen, M. (2018). Evaluation of an ear-tag-based accelerometer for monitoring rumination in dairy cows. *Journal of Dairy Science,* 101: 3398–3411.

Schrade, S., Zähner, M., Poteko, J., Zeyer, K., Mohn, J., Steiner, B. & Keck, M. (2016). Experimental dairy housing for comparative emission measurements. In: *25th International Scientifc Symposium on Nutrition of Farm Animals Zadravec-Erjavec Days 2016* (eds. by Ceh T & Kapun S), pp. 185-189, Radenci.

Toaff-Rosenstein, R.L., Velez, M. & Tucker, C.B. (2017). Technical note: Use of an automated grooming brush by heifers and potential for radiofrequency identification-based measurements of this behavior. *Journal of Dairy Science,* 100: 8430–8437.

Weary, D.M., Huzzey, J.M. & von Keyserlingk, M.A.G. (2009). Board-invited review: Using behavior to predict and identify ill health in animals. *Journal of Animal Science,* 87: 770–777.

Zehner, N., Umstatter, C., Niederhauser, J.J. & Schick, M. (2017). System specification and validation of a noseband pressure sensor for measurement of ruminating and eating behavior in stable-fed cows. *Computers and Electronics in Agriculture,* 136: 31–41.

Session 15

Performance and Welfare of Dairy Animals (2)

Monitoring dairy cow behaviour to assess the effect of the housing and management system on animal welfare

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Abstract

Animal behaviour is one of the indicators of animal welfare and can be used to assess how different housing systems and management strategies affect the herd. Precision Livestock Farming tools can concretely help the farmer to monitor the behaviour of each individual animal in the barn. In order to implement these techniques, it is however necessary to define the relationships between cow behaviour and environmental parameters like temperature humidity index (THI). The present study aimed to evaluate the influence of climatic conditions (temperature and relative humidity) on the behaviour of a group of primiparous dairy cows.

Behavioural activities of all cows in the group were monitored by continuous video recording for 296 days (from September to July). To assess the effects of THI on the behaviours logistic regression analysis has been applied.

Results confirmed that THI can affect behavioural indices. The average daily lying index varied from 54% in winter to 43% in summer despite in the latter period THI values were much lower than the heat stress threshold (average THI: 74). The statistical approach adopted in this study, after a validation process through the use of accelerometers, could be the starting point for the development of predictive models. The use of this kind of tool, may offer a valid support to the farmer to monitor cow behaviours and to adopt mitigation measures in case of heat stress.

Keywords: Precision livestock farming, THI, dairy farming, lying time

Introduction

Lying down and resting behaviours are important for cow health, welfare, reproductive and productive status (Westin *et al.,* 2016). Changes in lying behaviour can be caused by diseases, housing conditions, stocking density and temperature and humidity (Kok *et al.*, 2015). Time spent lying down, the frequency of lying bouts, and the duration of individual bouts are considered to be useful indicators for animal welfare and have been used to evaluate stall comfort (Mattachini *et al.*, 2011).

Currently, lying behaviour can be assessed using continuous observations from video recordings or data from sensors (e.g. accelerometers) (Diosdado *et al.*, 2015; Kok *et al.,* 2015). Information on behaviours deriving from sensors can be used as a clear welfare indicator (Neethirajan *et al.*, 2017) and especially in the case of heat stress (Herbut & Angrecka, 2018), that seriously affects feed intake, cow body temperature, maintenance requirements and metabolic processes, feed efficiency, milk yield, reproductive efficiency, cow behaviour and disease incidence (Biffani *et al.,* 2016). Heat stress is an important threat to cattle breeding, especially in the Mediterranean basin (Moretti *et al.,* 2017), where overcrowding and the combination of high temperatures and high humidity can result in harsh conditions for dairy cows. Experiencing uncomfortable thermal conditions (due to the combination of high temperature and humidity) affects the capacity of cattle to

dissipate heat and leads to an increase in body temperature over the physiological limits (Formaggioni *et al.*, 2018).To this purpose, the temperature-humidity index (THI), an index that combines the simultaneous effect of temperature and humidity, has been widely used to evaluate heat stress in this species (Abeni & Galli, 2017; Herbut & Angrecka, 2018; Moretti *et al.*, 2017).

Since dairy cows modify their behaviour as a function of the temperature and the humidity, in terms of drinking, feed intake, and movement (Polsky & von Keyserlingk, 2017), the present study aimed to evaluate the influence of climatic conditions (temperature and relative humidity) on the behaviour of a group of primiparous dairy cows using digital images.

Material and methods

2.1 Animals, Housing and Cow Selection

Data were collected at the experimental farm A. Menozzi (Landriano, Italy; 45°19'16.5"N, 9°15'56.4"E) of the University of Milan, for almost a year. Dairy cows were housed in a freestall pen in a loose-housing layout with a total of 130 cubicles having rubber mats and 106 feeding places. A total mixed ration (TMR) was delivered once daily beginning at approximately 10.00 h. Cows were milked twice daily at approximately 08.30 and 21.00 h.

In the study, a total of 35 primiparous dairy cows during all lactation period were selected. For each cow, the monitoring period started from the first days after calving.

2.2 Behavioural and Environmental Data

All behaviours of the cows were continuously monitored using a video recording system throughout the study, except at the times when the cows were milked. The video surveillance system consisted of four infrared (IR) day/night weather-proof varifocal cameras with 42 IR LED for night vision (420SS-EC5, Vigital Technology Ltd., Sheung Wan, Hong Kong) connected to a recording personal computer. The cameras (four for each farm) were placed about 5 m above the pen floor. Behaviours recorded were lying, standing, feeding, drinking and perching.

To understand the effect of the temperature and humidity on cow behaviours, four data loggers (HOBO U12 Temp/RH/Light/External Data Logger, Onset Computer Corporation, Bourne, MA, USA) were placed in four separate locations at a height of about 2 m above the floor and data were collected for 296 days (from September to July). The recording interval for microclimatic data was set at 30 min. Temperature–humidity indices (THI) were calculated according to Yousef (1985).

An average THI was determined from the calculated THI for each position in the barn.

2.3 Data Editing and Statistical Analysis

Dataset included video recordings for 296 days (from September to July). During the manual labelling of video recordings, all the activities performed by the herd were recorded once per hour, counting the number of cows performing a specific behaviour. Labelling procedure was performed by five trained labellers with a inter-observer reliability of 97.09% agreement for the behavioural activities analysed.

Lying behaviour (LYI) was considered when the cow occupied the cubicle laying on it. The feeding (FEE) and drinking behaviour (DRI) were considered when the cow was in the feed bunk and at the drinker, respectively. A behaviour was considered as standing (STA) when cows were in the alleys. Perching (PER) was classified when cows had the front legs in the cubicle and the rear legs were in the alley.

Behavioural data were combined with environmental parameters, using the date and the hour as a merging criterion, successively. Months were grouped in seasons and hours of the day were grouped in four classes (morning, afternoon, evening and night).

THI was subdivided in five classes (<50; 50-57; 57-62; 62-69; >70) to evaluate differences in the behaviour due to relatively small variation of THI. Furthermore, the THI class 57 - 62 (between 13–19 °C at 50% of relative humidity) was considered as a reference class for the analysis, because it represents the centre of cows thermal comfort zone, that ranges between 5–25 °C (Correa-Calderon *et al.*, 2004).

Multivariable logistic regression models (Proc LOGISTIC, SAS, Cary, NC, USA) were built to test the probability of changes in lying time according to THI classes (using as a reference the class 57 - 62), seasonality and excluding data collected in night-time hours (from 00.00 h to 06.00 h). The results of this kind of analysis are the Odds Ratios (ORs). ORs show the association between the occurrence of a behaviour (e.g. lying or standing) and the environmental parameters (e.g. THI, season, day part).

Finally, results were plotted as forest plot that allows the comparison of the results of the logistic regression models.

Results and discussion

The average time spent lying, standing and perching in relation to the average THI is reported in Figure 1.

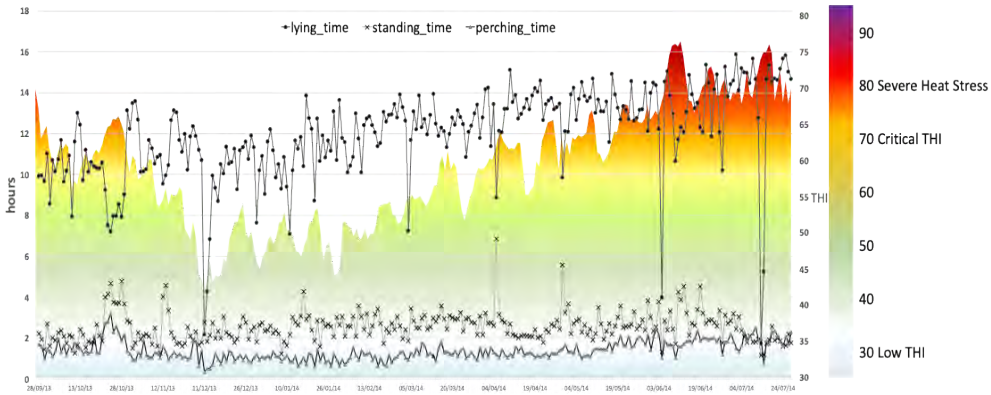

Figure 1. Average time spent lying, standing and perching in relation to the daily average THI

Results of the LOGISTIC Procedure showed that all the effects included in the model (THI classes, the part of the day and the season) were highly significant ($P > 0.001$), showing a relevant effect of climatic condition on cow behaviours.

In particular, as it is possible to see from Tables 1–4, all the classes of THI have a significant effect on the four activities examined. The Odds Ratios (ORs) reported in Figures 2-5 for the four activities, show the measure of association between the THI and the recorded behaviours. ORs represent the odds of having the cow, or the group of cows, lying in the cubicle compared to the odds of having the cow, or the groups of cows, performing other behaviours (standing, feeding, drinking and perching), given the same THI. ORs higher than 1 means that there is a high association between the behaviour and the class of THI, while, ORs lower than the unit means a reduced association between the behaviour and

the THI. In Tables 1 - 4 also, 95% Confidence Interval (95% CI) are reported. The 95% CI is used to estimate the precision of the OR. A large CI indicates a low level of precision of the OR, whereas a small CI indicates a higher precision of the OR. 95% CI is also used as a proxy for the presence of statistical significance if it does not overlap the null value (e.g. OR = 1) (Szumilas, 2010).

ORs lower than 1 in Tables 1-4 represent the lower incidence of standing, feeding, drinking and perching behaviours compared to the lying behaviour for the given class of THI. As an example, standing time is lower compared to lying time when the THI is lower than 57 (THI < 50: OR = 0.686; THI 50-57: OR = 0.85), while when cows experienced THI higher than 62, they prefer to stand rather than lie in the cubicle (THI 62-69: OR = 1.15; THI > 70: OR = 1.087). The same trend is reported graphically in Figure 2.

Table 1. Odds ratio estimate for the variable standing collected with the analysis of digital images

Variable	Estimate	SE	Odds ratio	95% CI	P-value
Intercept	-1.06	0.029			<.0001
THI <50	-0.38	0.026	0.686	0.643-0.731	<.0001
THI 50-57	-0.16	0.021	0.85	0.808-0.894	<.0001
THI 62-69	0.14	0.033	1.15	1.105-1.198	<.0001
THI >70	0.08	0.029	1.087	1.028-1.149	0.004

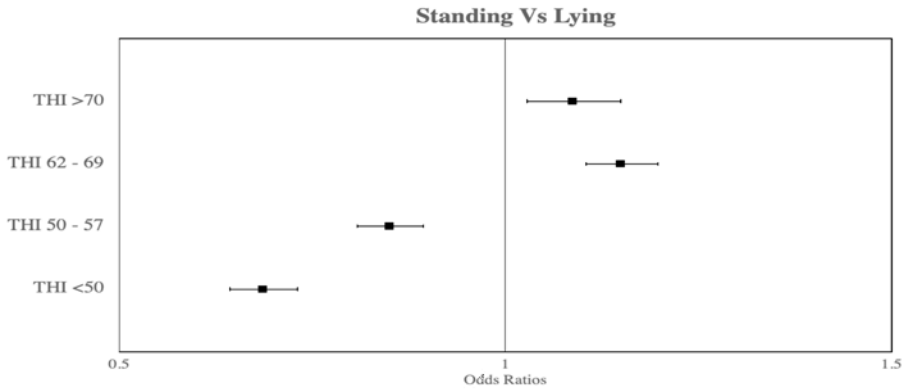

Figure 2. Forest Plot of the Odds Ratio of the Variable Standing vs Lying

Similar results were obtained for the perching behaviour (Table 2). Indeed, the incidence of the perching behaviour compared to the lying behaviour was highly associated to hotter conditions (THI 62-69: OR = 1.174; THI >70: OR = 1.245). Results for standing and perching behaviours are in line with literature, since those behaviours are commonly adopted by cows to cope with heath stress (Allen *et al.*, 2015; Herbut & Angrecka, 2018).

Table 2. Odds ratio estimate for the variable perching collected with the analysis of digital images

Variable	Estimate	SE	Odds ratio	95% CI	P-value
Intercept	-2.043	0.04			<.0001
THI <50	-0.3761	0.046	0.687	0.628-0.751	<.0001
THI 50-57	-0.1792	0.035	0.836	0.781-0.895	<.0001
THI 62-69	0.1607	0.027	1.174	1.113-1.239	<.0001
THI >70	0.2195	0.037	1.245	1.159-1.338	<.0001

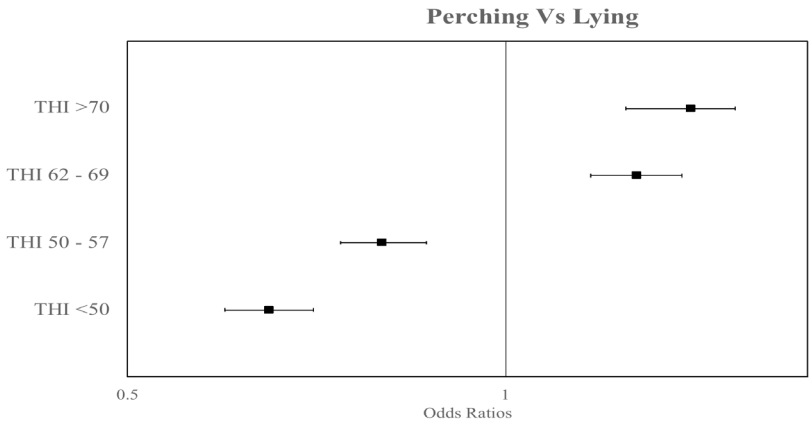

Figure 3. Forest Plot of the Odds Ratio of the Variable Perching vs Lying

Also, feeding and drinking behaviours are highly affected by climatic conditions. In Table 3 and Figure 4, it is possible to notice that lower THI (below 57) reduce the feeding behaviour (THI < 50: OR = 0.57; THI 50-57: OR = 0.826) compared to the lying behaviour. In other words, cows prefer to lie down in the cubicle rather than going to the feed bunk when temperatures are too low (Table 3). The same situation can be observed when the temperature is too high (THI above 70) and may lead to lack of appetite.

Table 3. Odds ratio estimate for the variable feeding collected with the analysis of digital images

Variable	Estimate	SE	Odds ratio	95% CI	P-value
Intercept	-0.2179	0.022			<.0001
THI <50	-0.562	0.025	0.57	0.543-0.598	<.0001
THI 50-57	-0.191	0.019	0.826	0.795-0.858	<.0001
THI 62-69	0.037	0.016	1.038	1.006-1.071	0.020
THI >70	-0.1966	0.024	0.822	0.784-0.861	<.0001

As expected, drinking behaviour (Table 4) was highly associated to climatic conditions. Also, for this behaviour, the highest incidences were observed when the THI was greater than 62 (THI 62-69: OR = 1.432; THI >70: OR = 1.119).

Table 4. Odds ratio estimate for the variable drinking collected with the analysis of digital images

Variable	Estimate	SE	Odds ratio	95% CI	P-value
Intercept	-2.4606	0.051			<.0001
THI <50	-0.5195	0.060	0.595	0.529-0.669	<.0001
THI 50-57	-0.1467	0.046	0.864	0.79-0.944	0.001
THI 62-69	0.3593	0.035	1.432	1.337-1.534	<.0001
THI >70	0.1127	0.052	1.119	1.012-1.238	0.029

In general, above THI values of 70 there is a decrease in the ORs for the behaviours of standing, feeding and drinking compared to THI values between 62–69 (Figures 2, 4 and 5).

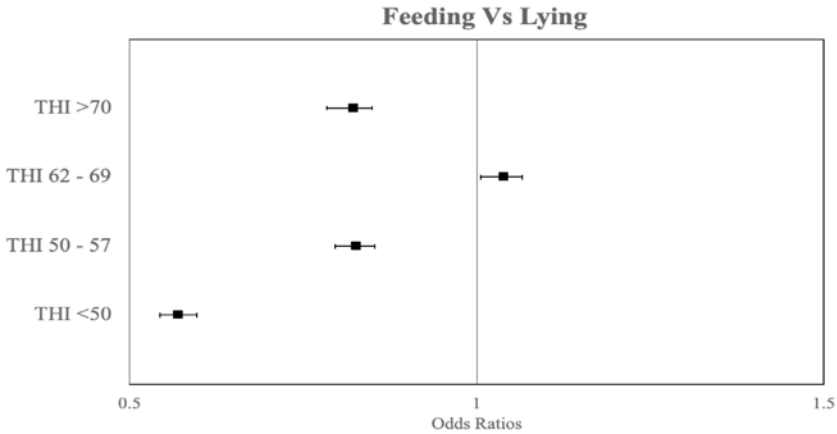

Figure 4. Forest Plot of the Odds Ratio of the Variable Feeding vs Lying

Figure 5. Forest Plot of the Odds Ratio of the Variable Drinking vs Lying

These situations can occur, since in cows, depression in feed consumption is the most important reaction to heat exposure due to the suppressive nerve impulses on the hypothalamus in an attempt to create less metabolic heat (Habeeb *et al.*, 2018).

Furthermore, in extreme cases of heat stress, a cow's thirst can be inhibited or completely depressed by altered mental states induced by hyperthermia (Polsky & von Keyserlingk, 2017).

Conclusions

The present study aimed to evaluate the influence of climatic conditions (temperature and relative humidity) on the behaviour of a group of dairy cows. Results of the analysis showed the clear and well-known association between the climatic conditions and lying, standing, feeding, drinking and perching behaviours. The statistical approach adopted in this study, after a validation process through the use of accelerometers, could be the starting point for the development of predictive models. Such type of mathematical models could be used to give an early warning on behavioural abnormalities linked to climatic conditions on the single cow or on the entire herd, compared to historical data.

References

Abeni, F., & Galli, A. (2017). Monitoring cow activity and rumination time for an early detection of heat stress in dairy cow. *International Journal of Biometeorology*, *61*(3): 417–425. https://doi.org/10.1007/s00484-016-1222-z.

Allen, J.D., Hall, L.W., Collier, R.J., & Smith, J.F. (2015). Effect of core body temperature, time of day, and climate conditions on behavioral patterns of lactating dairy cows experiencing mild to moderate heat stress. *Journal of Dairy Science*, *98*(1): 118–127.

Biffani, S., Bernabucci, U., Vitali, A., Lacetera, N., & Nardone, A. (2016). Short communication: Effect of heat stress on nonreturn rate of Italian Holstein cows. *Journal of Dairy Science*, *99*(7): 5837–5843. https://doi.org/https://doi.org/10.3168/jds.2015–10491.

Correa-Calderon, A., Armstrong, D., Ray, D., DeNise, S., Enns, M., & Howison, C. (2004). Thermoregulatory responses of Holstein and Brown Swiss heat-stressed dairy cows to two different cooling systems. *International Journal of Biometeorology*, *48*(3): 142–148.

Diosdado, J.A.V., Barker, Z.E., Hodges, H.R., Amory, J.R., Croft, D.P., Bell, N.J., & Codling, E.A. (2015). Classification of behaviour in housed dairy cows using an accelerometer-based activity monitoring system. *Animal Biotelemetry*, *3*(1): 15.

Formaggioni, P., Summer, A., Gottardo, F., & Lora, I. (2018). Impact of heat stress on milk and meat production. *Animal Frontiers*, *9*(1): 39–46. https://doi.org/10.1093/af/vfy026.

Habeeb, A.A.M., El-Tarabany, A.A., Gad, A.E., & Atta, M.A. (2018). Negative Effects of Heat Stress on Physiological and Immunity Responses of Farm Animals. *Change*, *16*(2.0): 0–2.

Herbut, P., & Angrecka, S. (2018). Relationship between THI level and dairy cows' behaviour during summer period. *Italian Journal of Animal Science*, *17*(1): 226–233.

Kok, A., van Knegsel, A.T.M., van Middelaar, C.E., Hogeveen, H., Kemp, B., & de Boer, I.J.M. (2015). Validation of sensor-recorded lying bouts in lactating dairy cows using a 2-sensor approach. *Journal of Dairy Science*, *98*(11): 7911–7916.

Mattachini, G., Riva, E., & Provolo, G. (2011). The lying and standing activity indices of dairy cows in free-stall housing. *Applied Animal Behaviour Science*, *129*(1): 18–27. https://doi.org/https://doi.org/10.1016/j.applanim.2010.10.003.

Moretti, R., Biffani, S., Chessa, S., & Bozzi, R. (2017). Heat stress effects on Holstein dairy cows' rumination. *Animal*, *11*(12): 2320–2325. https://doi.org/DOI: 10.1017/S1751731117001173.

Neethirajan, S., Tuteja, S.K., Huang, S.T., & Kelton, D. (2017). Recent advancement in biosensors technology for animal and livestock health management. *Biosens Bioelectron*, *98*: 398–407. https://doi.org/10.1016/j.bios.2017.07.015.

Polsky, L., & von Keyserlingk, M.A.G. (2017). Invited review: Effects of heat stress on dairy cattle welfare.

Journal of Dairy Science, *100*(11): 8645–8657. https://doi.org/https://doi.org/10.3168/jds.2017–12651.

Szumilas, M. (2010). Explaining odds ratios. *Journal of the Canadian Academy of Child and Adolescent Psychiatry = Journal de l'Academie Canadienne de Psychiatrie de l'enfant et de l'adolescent*, *19*(3): 227–229. Retrieved from https://www.ncbi.nlm.nih.gov/pubmed/20842279.

Westin, R., Vaughan, A., de Passillé, A.M., DeVries, T.J., Pajor, E.A., Pellerin, D., Siegford, J.M., Vasseur, E., & Rushen, J. (2016). Lying times of lactating cows on dairy farms with automatic milking systems and the relation to lameness, leg lesions, and body condition score. *Journal of Dairy Science*, *99*(1): 551–561. https://doi.org/https://doi.org/10.3168/jds.2015–9737.

Yousef, M.K. (1985). *Stress physiology in livestock. Volume I. Basic principles.* CRC press.

Random forest regression for estimating dry matter intake of grazing dairy cows

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Abstract

The understanding of individual feed intake of grazing cows is essential for monitoring the nutrient intake of the animal, to calculate feed efficiency and increase animal and pasture productivity as well as tailored herd and pasture management. However, the measurement of individual herbage dry matter intake (hDMI) of individual cows is laborious and may be challenging in commercial grass-based dairy systems. The aim of this study was to assess the application potential of machine learning algorithms (random forest) to estimate the individual hDMI of grazing dairy cows in an intensive grazing management system using animal behaviour characteristics. This study was performed at a research farm on n = 41 animals with the established reference value for measuring feed intake based on the n-alkane technique. The database for model development included individual cow information, on-field grass measurements, grass quality as well as detailed individual cow behavioural characteristics based on the RumiWatchSystem. Random forest regression was used to predict hDMI. Recursive feature elimination (RFE) was used to select the best subset of predictors to be included in the model. To overcome issues associated with the relatively small sample size of n = 68 weekly values in total a nested cross-validation procedure was implemented. Results showed that RF has good potential for the prediction of hDMI in grazing dairy cattle. However, further studies are required to fully assess performance of this method and identify new potential predictors for hDMI.

Keywords: grazing, dairy cattle, dry matter intake, random forest, cross validation

Introduction

Pasture growth and utilisation have been reported as the main factors affecting profitability of pasture-based dairy farms (Hanrahan *et al.*, 2018). A better understanding of individual herbage dry matter intake (hDMI) at pasture has the potential to improve herd and grassland management. However, conventional methods for hDMI estimation, such as the n-alkane technique, are laborious and require specific equipment (Hellwing *et al.*, 2015). In recent years, PLF technologies such as behaviour sensors have become largely available to dairy producers and can provide fast and easy access to a wide range of information about both pasture and cows (Shalloo *et al.*, 2018). The aim of this study was to assess the application of a machine learning algorithm (random forest) for the estimation of individual hDMI of grazing dairy cows based on readily available data and information collected by PLF sensors.

Material and methods

The study was performed during the spring and summer of 2016 (27 March 2016 – 31 July 2016) at the Teagasc's research farm in Moorepark, Fermoy, Ireland. Forty-one spring calving dairy cows were included in the study, 24 of them were Holstein-Friesian, nine were Jersey and eight were crossbreeds. Ten primiparous cows and 31 multiparous cows were included, with an average parity of 2.57±1.41. All cows calved between 26 January

2016–28 February 2016. The body weight (BW) of cows included in the study was 470±65 kg while milk yield was 20.8±2.3 kg/cow/day.

During the experiment, cows grazed a perennial ryegrass-based pasture with no supplementary feeding. Cows were milked twice daily (at 7:00 and 14:30) and fresh pasture was offered after each milking. As the cows were involved in another on-going experiment regarding restricted pasture allocation (Werner *et al.*, 2019), a wide range of daily herbage allowances (DHA) was available. On average DHA was 13.6 kgDM/cow/day, ranging from 9.0–17.0 kgDM/cow/day (3.5 cm above the ground). Pre- and post-grazing compressed grass heights (PREGH and POSTGH) were measured daily using a rising plate meter (Jenquip, Fielding, New Zealand). The PREGH and POSTGH were 8.8±1.9 cm and 3.8±1.0 cm, respectively. Representative grass samples from each paddock were collected weekly and sent to an external lab for analysis. Results showed a crude protein (CP) content of 21.4±1.7%, 23.3±3.1% acid detergent fibre (ADF), 40.1±2.4% neutral detergent fibre (NDF), 26.3±2.7% non-forage carbohydrates (NFC) and 11.84±0.17 MJ/kgDM metabolizable energy (ME).

The experiment consisted of two observation periods, which lasted five weeks during spring and one week during summer. During observations, cows were fitted with the RumiWatchSystem (Itin+Hoch GmbH, Liestal, Switzerland), which consisted of a noseband sensor and a pedometer. This system was capable of monitoring cows' grazing behaviour, rumination and physical activity in a detailed and accurate manner (Werner *et al.*, 2018). Behaviour parameters measured by the RumiWatchSystem and retained in the final dataset are reported and described in Table 1.

Table 1. Behaviour parameters measured by the RumiWatchSystem and retained in final model for analysis

Parameter (unit of measure)	RumiWatch Output	Mean±SD
Ruminating chews frequency (n/min)	CHEWSPERMINUTE	49.5±5.8
Ruminating bouts started (n/day)	RUMIBOUTSTART	13.6±2.0
Ruminating time (min/day)	RUMINATETIME	456±65
Grazing bites (n/day)[1]	EATBITE	33,413±4,818
Feeding bite frequency (n/min)[2]	EAT1CHEW/EAT1TIME	74.8±3.6
Grazing bite frequency (n/min)[1]	EATBITE/EATTIME	54.6±5.3
Grazing bouts (n/day)	GRAZINGSTART	8.0±1.6
Total feeding time (min/day)	EATTIME	611±51
Feeding time with head down (min/day)	EAT1TIME	512±56
Feeding time with head up (min/day)	EAT2TIME	99±33
Other activities time (min/day)	OTHERACTIVITYTIME	368±83
Other chews (n/day)	OTHERCHEW	1,186±401
Walking time (min/day)	WALKTIME	95±20
Laying bouts (n/day)	LAYDOWN	7.7±1.7
Laying time (min/day)	LAYTIME	517±83

[1]Grazing bites are defined as prehension bites or jaw movements for ripping the grass; [2]Feeding bites are defined as all the feeding jaw movements taken with head down

Individual hDMI was estimated with the n-alkane technique (Dillon & Stakelum, 1989). Cows were dosed with a C32 n-alkane marker. Faecal samples were collected twice daily in the paddocks, before both am and pm milking and analysed in a lab. Estimation of hDMI was based on the amount of marker found in faeces and yielded weekly average values for each individual. As the n-alkane technique has demonstrated reliable estimates of individual intake (Wright *et al.*, 2019), values obtained with this method were used as the reference hDMI.

Data preparation and analysis

A dataset containing all possible predictors and reference hDMI was built. As the reference hDMI was only available as weekly means, all other data originally recorded in different time frames were converted to obtain weekly values. Initially, 103 variables were acquired which were then filtered to improve model prediction performance. Twenty-one descriptors were excluded for having the same value for more than 95% of the dataset. Fifty-two redundant variables were filtered off until no remaining pair-wise correlations exceeded $r_p = 0.9$ (Pearson correlation). As RF cannot deal with missing values, incomplete observations had to be removed as well. The final dataset consisted of 68 cow-week observations (rows) and 30 variables (columns) including cow characteristics (cow ID, breed, BW, parity, DIM), grass field measurements (DHA, PREGH and POSTGH), grass lab analysis (NDF, ADF, NFC, CP, ME), cows' behaviour data (CHEWSPERMINUTE, RUMIBOUTSTART, RUMINATETIME, EATBITE, EAT1CHEW/EAT1TIME, EATBITE/EATTIME, GRAZINGSTART, EATTIME, EAT1TIME, EAT2TIME, OTHERACTIVITYTIME, OTHERCHEW, WALKTIME, LAYDOWN, LAYTIME; Table 1) and hDMI.

Data analysis was performed using the open source R statistical software (R Core Team, 2018). Random forest (RF) regression was used to predict hDMI. The RF model is a machine learning method for classification and regression analysis that uses an ensemble of randomised decision trees to define its output (Breiman, 2001). To overcome issues associated with the relatively small sample size (n. 68), avoid overfitting and obtain a robust evaluation of model performance, a nested cross-validation (CV) procedure was implemented (Figure 1). This method consisted of an inner and outer repeated CV loop analysis, each with three folds and ten repetitions. The inner CV was used to tune model parameters, subset predictors and select the best model. Then, generalisation error was estimated by averaging the test set scores over several dataset splits in the outer CV loop. In the inner CV, recursive feature elimination was used to select the best subsets of predictors to be included in the models. Variable importance was computed for any variable included in the models selected in the inner CV and described the deterioration in prediction accuracy of the model when excluding that particular descriptor. Root-mean-square error (RMSE) and explained variance were used to evaluate model performance in both the inner and outer CV loops.

Results and discussion

The hDMI of cows included in the experiment, as estimated with the n-alkane method, was 16.35±4.4 kgDM/cow/day. The RF models produced were capable of explaining 64.1±8.5% of the variance in hDMI, with an average root-mean-square error (RMSE) of 2.66±0.37 kgDM/cow/day (Outer CV; Table 2).

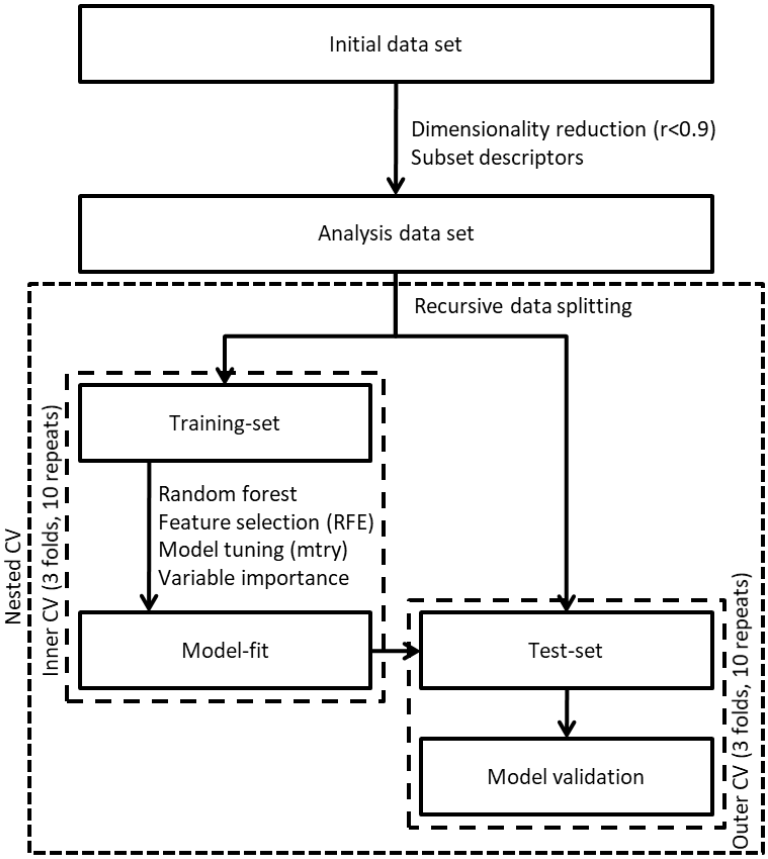

Figure 1. Workflow of the data preparation and modelling process based on a nested CV procedure

Table 2. Performance estimates of the random forest models in the inner (training set) and outer (test set) CV loops

	Inner CV	Outer CV
mtry[1]	3.30±1.26	
n. of predictors	10.57±3.86	
Explained variance (%)	67.3±13.4	64.1±8.5
RMSE[2]	2.63±0.55	2.66±0.37

[1]number of variables randomly sampled as candidates at each split; [2]root-mean-square error

By recursively splitting the dataset in train and test sets, the nested CV procedure ensured data used to train the model was not used to test it providing a robust evaluation of model performance (Cawley & Talbot, 2010). The relatively large variation in model performance metrics for both the inner and outer CV loops shows that RF may produce instable results when dealing with small sample sizes. The method employed showed an effective tool to overcome this issue as variation in model performance is captured and can therefore be

evaluated. Also, consistency between performance measured in the inner and outer CV loops indicates the method used was capable of preventing overfitting.

The number of predictors retained in the models by RFE (inner CV) was 10.57±3.86 (Table 2). Figure 2 shows the improvement in model performance (RMSE) with increasing number of variables included during the model training process. Variable importance analysis (Figure 3) showed that grass quality parameters (NDF, ADF, NFC) are the most important predictors of hDMI. In the current study, grass quality was more important than DHA and PREGH and POSTGH in predicting hDMI. These outcomes confirm that maintaining high grass quality is key to maximise hDMI at pasture (Dillon, 2006). Cows' bodyweight, DIM and parity were also highly associated with hDMI. This indicates that a high variation in hDMI may exist among individuals. Overall, behavioural measures were shown to affect hDMI to a rather limited extent with just two variables (EAT1CHEW/EAT1TIME and LAYTIME) ranked among the ten most important predictors. Surprisingly, although a number of grazing bites is thought to be strictly related to hDMI (Umemura *et al.*, 2009; Oudshoorn *et al.*, 2013), EATBITE was among the least important variables being excluded from one-third of the models trained in the inner CV. Obviously this suggests that predicting hDMI based on behavioural measures alone may pose some challenges.

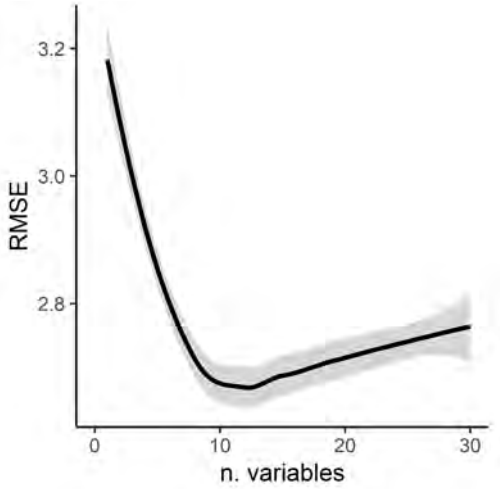

Figure 2. Root mean square error (RMSE) vs number of variables included in the models during model training process (inner CV)

In a recent study Rombach *et al.* (2019) also explored the possibility of modelling hDMI of grazing dairy cows based on behavioural data measured with the RumiWatchSystem and other accessible measures including cow characteristics, milk production and grass-related variables. Their results also highlighted that behavioural characteristics alone may not allow a sufficiently accurate estimation of individual hDMI.

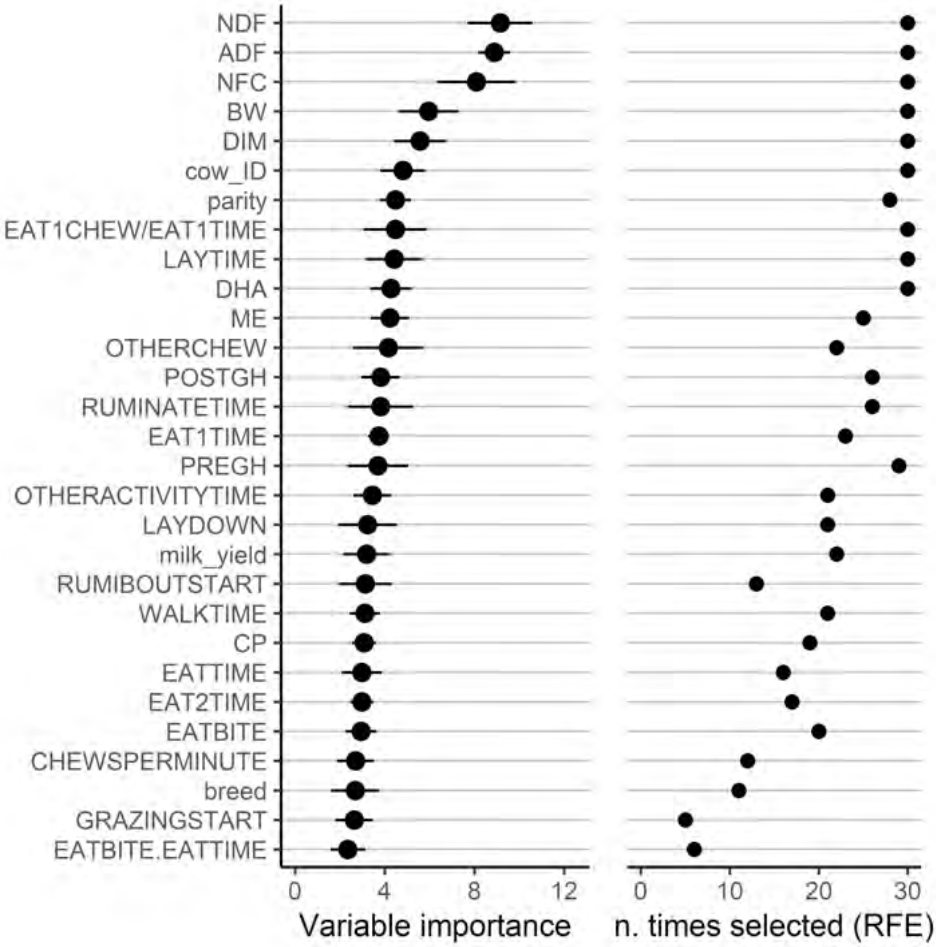

Figure 3. Random forest variable importance plot (left) and n. of times variables were selected by RFE (right) within the inner CV (train set)

Conclusions

Results showed that maintaining high grass quality is paramount to achieve high hDMI in pasture-based dairy systems. Random forest has been shown to have good potential for the prediction of hDMI in grazing dairy cattle. The nested CV procedure used in the current study allowed a robust estimation of model performance, even with a small sample size. Behavioural measurements showed limited importance in the RF model developed. Further research is required to identify new potential predictors and fully assess performance of machine learning algorithms for modelling of individual hDMI of grazing dairy cattle.

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References

Breiman, L. (2001). Random forests. *Machine Learning,* 45(1): 5–32.

Cawley, G.C. and Tablot, N.L. (2010). On Over-fitting in Model Selection and Subsequent Selection Bias in Performance Evaluation. *Journal of Machine Learning Research,* 11: 2079–2107.

Dillon, P. (2006). Achieving high dry-matter intake from pasture with grazing dairy cows. In: Elgersma A., Dijkstra J. and Tamminga S. (eds.) *Fresh Herbage for Dairy Cattle*, 1–26. Springer. Printed in the Netherlands. pp. 1–26.

Dillon, P. and Stakelum, G. (1989). Herbage and dosed alkanes as a grass measurement technique for dairy cows. *Irish Journal of Agricultural Research* 28,104 (Abstr.).

Hanrahan, L., McHugh N., Hennessy, T., Moran, B., Kearney, R., Wallace, M. and Shalloo, L. (2018). Factors associated with profitability in pasture-based systems of milk production. *Journal of Dairy Science,* 101(6): 5474–5485.

Hellwing, A.L.F., Lund, P., Weisbjerg, M.R., Oudshoorn, F.W., Munksgaard, L. and Kristensenc, T. (2015). Comparison of methods for estimating herbage intake in grazing dairy cows. *Livestock Science,* 176: 61–74.

Oudshoorn, F.W., Cornou, C., Hellwing, A.L.F., Hansen, H.H., Munksgaard, L., Lund, P. and Kristensen, T. (2013). Estimation of grass intake on pasture for dairy cows using tightly and loosely mounted di- and tri-axial accelerometers combined with bite count. *Computers and Electronics in Agriculture* 99: 227–235.

R Core Team (2018). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Rombach, M., Südekum, K.-H., Münger, A. and Schori, F. (2019). Herbage dry matter intake estimation of grazing dairy cows based on animal, behavioral, environmental, and feed variables. *Journal of Dairy Science,* 102: 1–15.

Shalloo, L., O' Donovan, M., Leso, L., Werner, J., Ruelle, E., Geoghegan, A., Delaby, L. and O'Leary, N. (2018). Review: Grass-based dairy systems, data and precision technologies. *Animal*, 12(s2): s262-s271.

Umemura, K., Wanaka, T. and Ueno, T. (2009). Technical note: Estimation of feed intake while grazing using a wireless system requiring no halter. *Journal of Dairy Science,* 92: 996–1000.

Werner, J., Leso, L., Umstatter, C., Niederhauser, J., Kennedy, E., Geoghegan, A., Shalloo, L., Schick, M. and O'Brien, B. (2018). Evaluation of the RumiWatchSystem for measuring grazing behaviour of cows. *Journal of Neuroscience Methods,* 300: 138–146.

Werner, J., Umstatter, C., Kennedy, E., Grant, J., Leso, L., Geoghegan, A., Shalloo, L., Schick, M. and O'Brien, B. (2019). Identification of possible cow grazing behaviour indicators for restricted grass availability in a pasture-based spring calving dairy system. *Livestock Science,* 220: 74–82.

Wright, M.M., Lewis, E., Garry, B., Galvin, N., Dunshea, F.R., Hannah, M.C., Auldist, M.J., Wales, W.J., Dillon, P. and Kennedy, E. (2019). Evaluation of the n-alkane technique for estimating herbage dry matter intake of dairy cows offered herbage harvested at two different stages of growth in summer and autumn. *Animal Feed Science and Technology,* 247: 199–209.

Comparison of three gradients of grazed grass in dairy cows' diet in terms of environmental and zootechnical performances

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Abstract

Climatic change induces challenges in grazing management, which could tempt farmers to keep their cows indoors. To assess the environmental and economic impact of diets with different percentages of grazed grass, 33 Holstein cows in early lactation were divided into three groups from 27 April to 7 July 2018. These groups were allocated an increasing proportion of grazed grass in their diet. No access to grazed grass was possible for Group 1 (0%), while Group 2 and 3 were granted access to pasture 21w. Group 2's (100%) diet was composed of 100% grass. Group 3 (50%) received silage in the barn as well as grazed grass. The access to pasture was adapted to achieve a proportion of 50% grass in the diet. Sward height was measured every week with an electronic rising plate meter (EC 20®), and the nutritional composition of grazed grass was evaluated. All the groups' diet was complemented with concentrates delivered by the automatic concentrate supplier, where the Guardian® was located in order to measure the methane emitted at each visit. Methane emissions were also assessed by predictions based on the mid infra-red (MIR) spectrum of milk samples. Animal performance was recorded and the milk carbon footprint was estimated by the Feedprint®. No difference in milk yield between the groups was recorded. Predictions based on the MIR spectra analysis showed a slight decrease in methane emission per cow and per day in the 100% group, but this decrease was not confirmed by the breath samples measurements. The feeding costs were in favour of the 100% group. The carbon-footprint of the milk produced with 100% or 50% of grazed grass was lower than for the zero-grazing cows.

Keywords: grazing, methane emissions, milk carbon footprint, grazing practices, dairy cows

Introduction

Grasslands are recognised as playing the role of carbon sink, allowing the mitigation of a substantial amount of greenhouse gases from the agricultural sector (Soussana *et al.*, 2010). Yet, grazing may contribute to the preservation of these areas. A survey undertaken during the Life project Dairyclim showed that the difficulty in managing grazing was a decisive factor for stopping grazing (Lessire *et al.*, 2018_a). Other invoked reasons for abandoning this practice are economic and climatic. Especially in intensive farms, farmers prefer to feed the cows with a controlled diet indoors, even during the summer period. In this context, the aim of this trial was to assess how the percentage of grazed grass in cows' diet could influence production performances and environmental indicators such as methane emissions and the carbon footprint (CF) of milk. The economic impact of grazing was also estimated through the calculation of feeding costs linked to the different diets.

Material and methods

The study was conducted at the Centre of Agronomic Technologies (CTA) in Belgium from 19 May 2018–6 July 2018, after a three week transition period. Thirty-three Holstein cows in early lactation were divided into three groups balanced on milk yield (MY), days in milk (DIM) and lactation number (LN) (Table 1). Each group received a different amount

of grazed grass in the ration. The first group was kept indoors. The percentage of grass was therefore 0%. The second group (100%) had access to pasture. For the third group, the allocation of grazed grass was estimated at 50% on the basis of sward height measurements and grazing time. This group was offered a partial mixed ration in the barn. The different rations are described in Table 2.

Table 1. Description of the three groups at the beginning of the trial

	Nbr cows	DIM	LN	MY (kg cow^{-1}d^{-1})
Group 0%	11	133 ± 58	1.9 ± 0.9	29.5 ± 4.9
Group 50%	11	134 ± 59	2.1 ± 1.0	28.0 ± 6.8
Group 100%	11	133 ± 43	2.0 ± 0.9	26.4 ± 6.0

Abbreviations: DIM: days in milk; LN: lactation number; MY: milk yield

All the rations were calculated to ensure energy inputs of 20 KVEM (142 NEL). The Groups 0 and 50% received a ration mainly composed of forages: (Group 0 - 78.8% and Group 50 - 35%).

Table 2. Description of the diet allocated to each group

% DMI	Group 0% grazing	Group 50% grazing	Group 100% grazing
Grass silage	33.7	-	-
Alfalfa silage	19.5	20	-
Maize silage	17.6	7	-
Beet pulp silage	8	8	-
Barley	4.2	4	-
Concentrate rich in protein (40%)	8.5	2	-
Grazed grass	-	50	91
Concentrates ACS	8.5	9	9
Total DMI	21.6	20.4	19.8
Foreseen production	25.6 L (energy) 29.7 L (protein)	24.3 L (energy) 29.1 L (protein)	24.8 L (energy) 31.2 L (protein)

Abbreviations: ACS: automatic concentrate supplier; DMI: dry matter intake

The milk production and the concentrate consumption were recorded daily. Methane and CO_2 in breath samples were analysed by the Guardian® inserted in the automatic concentrate supplier. Methane productions were estimated following the method described by Haque *et al.* (2014). Individual milk samples were analysed twice per month for milk quality and for methane emissions, evaluated by milk spectra analysis based on the method described by Vanlierde *et al.* (2016).

Sward height was measured by the EC20® rising plate meter every week, in order to have an estimation of the grass availability and growth. The grass density was measured in a plot excluded from grazing, where grass was mowed on a 10 m length band every week.

The mowed grass was weighted and dried to calculate the grass density. The difference between sward height at the paddock entrance and exit, multiplied by the grass density and the surface of the paddock, provided the amount of grass eaten. This amount was then divided by the number of cows present on the paddock. Hand-plucked samples of grass were taken from the grazed paddock to determine its nutritional value. Meteorological data collected in a CTA weather station were also compiled to establish a link between the weather and the recorded grass growth.

The carbon footprint of feeding was estimated first by calculating the emission factors (kg-eq CO_2) of each feed component using the Feedprint® (Vellinga *et al.*, 2014), and then by adding them on a *prorata* basis of their % in the ration.

Feeding costs were calculated on the basis of purchase invoices. The silage production costs were estimated with the software "Dégâts du gibier", developed by Fourrages Mieux. The costs of grazed grass took into consideration the grass yield and the inputs to the pastures.

Descriptive data analysis was made using the software R (R-core Team 2016). Further analysis of methane emissions and animal performance was performed with Proc mixed (SAS 9.3). The model included a repeated statement (repeated days/subject animal) and a covariance analysis type cs.

$$Y_{ij} = \mu + Gr_i + NL_j + period_k + concentrate_l + DIM_m + period_k \text{ X } Gr_i + e_{ijklm}$$

where μ = the overall mean with fixed effects being Gr_i = group effect (i = 1–3 for group 1 = 0% to group 3 = 100%); NL: effect of lactation number (k =1–3 - 1 = primiparous, 2: 2^d lactation and 3 = over the second lactation); concentrate: concentrate consumption (kg $cow^{-1}.d^{-1}$); DIM_m:days in milk; $period_k$: period of measurement (May - June); $period_k$ X Gr_i: interaction group X $period_l$; $e_{ijklm:}$ residual error.

The model calculating the methane from breath samples also took in consideration the weight of the cow (kg), the sampling duration (min) and the number of samplings (n per day) in the automatic concentrate supplier.

Results

The meteorological data showed that the average temperature was higher than usual during the three months of the trials: 15.7 °C; 17.2 °C and 20.9 °C, respectively in May, June and July, compared to the values from the last 25 years: 12.9 °C; 15.45 °C and 17.5 °C, respectively in the same months. The rainfalls were more intense in May (78 mm in May vs 63.6 mm (25 year value)) while a drought occurred in July (10.1 mm vs 85.7 mm (25 year- value)). It must be noted that the precipitations observed in May and June (55.8 mm) were boosted by some days with intense rainfalls (>10 mm: 1 d in May – 2 d in June). These weather conditions favoured a higher grass growth rate in May and June (72.2 kg DM $ha^{-1}.d^{-1}$ in May; 40.3 kg DM $ha^{-1}.d^{-1}$ in June vs 56.4 kg DM $ha^{-1}.d^{-1}$ in May and 28.7 DM $ha^{-1}.d^{-1}$ in June 2017). During the trial period, the grass density was 280 DM ha^{-1}.

The mean grass intake was 16.2 kg DM for Group 100% and 10 kg DM for Group 50%. The nutritional values of grass were very good, with an energy supply of more than 1 KVEM (7.10 NEL) per kg DM and a protein content of over 20%. The values of 2017–2018 were very close (212 g kg DM^{-1} in 2018 vs 215 g kg DM^{-1} in 2017; VEM: 1,003 g kg DM^{-1} in 2018 vs 1,014 g kg DM^{-1} in 2017).

No statistical difference in milk yield (MY) or in energy corrected milk (ECM) yield was observed during the trials' period (Table 3). The methane emissions predicted by MIR were lower in the groups 100% and 50% compared to 0%, but the breath samples analysis did not confirm this result.

Table 3. Production recorded in the three groups during the trial period

	Group 0%	Group 50%	Group 100%	Signification stat
MY ($kg.cow^{-1}.d^{-1}$)	28.5 ± 1.3	27.2 ± 1.2	25.2 ± 1.3	ns
F%	3.78 ± 0.15	3.81 ± 0.15	3.60 ± 0.15	ns
Prot%	3.21 ± 0.07	3.18 ± 0.06	3.06 ± 0.07	ns
ECM ($kg.cow^{-1}.d^{-1}$)	27.5 ± 1.5	25.2 ± 1.4	24.2 ± 1.5	ns
Methane MIR ($g.cow^{-1}.d^{-1}$)	475 ± 9	440 ± 9	430 ± 9	*
Methane Guardian ($g.cow^{-1}.d^{-1}$)	453 ± 47	459 ± 31	472 ± 45	ns

Values are LS means ± SE.
Abbreviations: MY: milk yield; F: milk fat content; ECM: energy corrected milk; MIR: mid infra-red; NS: not significant; *: $p < 0.05$

The drought induced a reduction in the annual grass production so that the production costs of grazed grass were higher than in past years. For example, it was estimated at €60 per TDM in 2017, while it reached €90 per TDM in 2018. Despite this, the feeding costs of group 100% were approximately half those of 0% group. The 50% group had intermediary values (Table 4). The milk revenue was calculated on the basis of milk sale prices during the trials' period. Although we observed a lower milk, fat and protein production, the net margin was favourable for grazing groups.

The Carbon Footprint of the 100% and 50% ration was lower than that of the 0% (8,549 g $eqCO_2$ - 8,765 g $eqCO_2$ in groups 100% and 50%, respectively vs 10,360 g $eqCO_2$ in group 0%). Due to a lower MY in group 100%, the reduction of the Carbon Footprint g $eqCO_2$ per kg milk or per kg ECM was attenuated.

Table 4. Feeding costs, milk revenue and CF (Climate impact) calculated in the different groups

	Group 0%	Group 50%	Group 100%
Costs per cow.d	4.72 €	3.36 €	2.19 €
Costs per 100 kg milk	16.6 €	12.3 €	8.7 €
Sale price 1kg ECM	7.99 €	7.63 €	6.73 €
Net margin per cow.day	3.26 €	4.27 €	4.54 €
Total CF in daily diet	10,360 g $eqCO_2$	8,765 g $eqCO_2$	8,549 g $eqCO_2$
CF. kg $milk^{-1}$	356 g $eqCO_2$	322 g $eqCO_2$	339 g $eqCO_2$
CF. kg ECM^{-1}	369 g $eqCO_2$	361 g $eqCO_2$	353 g $eqCO_2$

Discussion

The grass growth rate observed in May and June allowed the group 100% to reach the same milk production level as groups 0% and 50%. Statistically, significant differences in methane emissions between treatments were not recorded, while these were recorded between Groups 0% and 100% using MIR predictions. This is consistent with the results observed in 2017 (Lessire *et al.*, 2018_b). Discrepancies in methane estimations obtained with the methods based on breath samples and MIR spectroscopy were also reported in another study (Shetty *et al.*, 2017) and could be attributed to several factors. One is that the methane in breath samples was measured over several days, and breath samples were taken every three seconds during the visits in the concentrate supplier. By comparison, only two milk samples per period were made. Finally, the methods to assess methane emissions are different: one is based on CH_4:CO_2 ratio in breath samples, and the other one on milk spectra analysis.

A slight decrease in the carbon footprint of produced milk was observed for both rations based on 100% and 50% grazed grass. It has to be noted that only the climate impact was taken into consideration and not the other indicators like LULUC changes or biodiversity index. This evaluation has yet to be completed.

Feeding costs were reduced as grazed grass intake increased. Even with the slight numerical reduction in MY for group 100%, costs were quite divided by two, allowing the group 100% to record the highest net margin.

Conclusion

Full grazing was beneficial in terms of economic performances. No statistically significant difference in zootechnical performance was observed. These results arose from the analysis of data collected in May and June, a period of intense growth rate. The follow up of the whole season suggests that these results would not be as beneficial in July and August because of droughts and their effect on grass growth. No difference in methane emissions per cow per day was registered. The carbon footprint calculated on the daily diet was favourable to the grazing groups but when reported by kg milk or kg ECM, this was less advantageous. Due to climatic uncertainties, complementing grass with forages has to be recommended to maintain animal performances, preserve grazing, and still contribute to decreasing the feeding costs and the environmental impact of dairy products.

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References

Haque, M.N., Cornou, C., Madsen, J. (2014). Estimation of methane emission using the CO_2 method from dairy cows fed concentrate with different carbohydrate compositions in automatic milking system. *Livestock Science,* 164(0): 57–66.

Lessire, F., Scohier, C., Kristensen, T., Reding, R., Lioy, R., Reuter, W., Elias, E., Dufrasne, I. (2018a) Grazing practices in three European countries: results of a survey in dairy farms. *Grassland Science in Europe*, 23: 619–621.

Lessire, F., Scohier, C., Dufrasne, I. (2018_b) Methane emissions and milk carbon footprint of dairy cows at grazing or fed with a concentrate diet. *Grassland Science in Europe,* 23: 616–618.

Shetty, N., Løvendahl, P., Lund, M.S., Buitenhuis, A.J. (2017). Prediction and validation of residual feed intake and dry matter intake in Danish lactating dairy cows using mid-infrared spectroscopy of milk. *Journal of Dairy Science,* 100: 253–264.

Soussana. J.F., Tallec. T., Blanfort. V. (2010). Mitigating the greenhouse gas balance of ruminant production systems through carbon sequestration in grasslands. *Animal*, 4(3): 334–350.

Vanlierde. A., Vanrobays, M.L.. Gengler. N.. Dardenne. P.. Froidmont. E.. Soyeurt. H.. … Dehareng. F. (2016). Milk mid-infrared spectra enable prediction of lactation-stage-dependent methane emissions of dairy cattle within routine population-scale milk recording schemes. *Animal Production Science*, *56*(3): 258–264.

Vellinga, T.H.V, Blonk, H., Marinussen, M., Zeist, W.J., van. Starman, D.A.J. Methodology used in FeedPrint: a tool quantifying greenhouse gas emissions of feed production and utilization (2014) Wageningen UR Livestock Research SN - 1570–8616.UR - http://edepot.wur.nl/254098.

Cooling regime timing set by bolus sensor mitigated heat stress in dairy cows

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Abstract

This research paper addresses the hypothesis that heat stress can be mitigated better by tailoring the cooling management to the cow's feeling.

In the summer, cooling systems help the high-yielding dairy cows to maintain body temperatures in intensive systems. Those cooling systems often function at a constant schedule, based on measurements of the environment and not of the animal itself. We propose a method utilising a dynamic cooling system, based on sensors that measure the cows' core temperatures. Thus, cooling can be activated when needed, and is most efficacious. A total of 30 lactating cows were randomly assigned to one of two groups which received two different evaporative cooling regimes: a control group, which received the common methods used in farms, time-based cooling; and an experimental group, which received the sensor-based cooling regime, that was changed every week (3 month in total) according to the cow's response to last week's change in terms of body temperature, as measured by reticulorumen boluses. The two groups of cows had similar milk yields (44.7 kg/d), but those in the experimental group had higher milk fat (3.65 vs 3.43%), higher milk protein (3.23 vs 3.13%), higher energy corrected milk (ECM, 42.84 vs 41.48 kg/d), higher fat corrected milk 4%; (FCM, 42.76 vs 41.34 kg/d) and shorter heat stress time (5.03 vs 9.46 hours/day) compared to the control. Dry matter intake was higher in the experimental group. Daily visits to the feed trough were less frequent, and with each visit lasting longer. The sensor-based cooling regime may be an effective tool to detect and ease heat stress in high-producing dairy cows under summer heat load in arid and semi-arid zones.

Keywords: Body temperature, eating behavior, PLF

Abbreviations:

ECM: energy corrected milk
FCM: fat corrected milk
PLF: precision livestock farming
RFI: residual feed intake
RFID: Radio frequency identification
RT: reticulorumen temperature
SB: sensor based
SE: standard error mean
TB: time based
THI: temperature humidity index
TMR: total mixed ratio
VT: vaginal temperature

Introduction

The industry loses millions of dollars annually due to reduced milk production during the summer months (St-Pierre *et al.*, 2003, West, 2003, Stull *et al.*, 2008, Ferreira *et al.*, 2016, Polsky and von Keyserlingk, 2017). Over and above, heat stress conditions are associated

with reduced eating, reduced feed efficiency, seriously impaired fertility (Schueller *et al.,* 2014, Mellado *et al.,* 2015) and cow discomfort (Honig *et al.*, 2012). The definition of the cow's thermoneutral condition, i.e. when the cow feels comfortable (because the heat production and the heat loss are balanced) varies: Piccione & Refinetti (2003) established the optimal body temperature as ranging from 38.6–39 °C, whereas Prendiville *et al.* (2002) suggested a lower range, of 38.2-39 °C.

Respiration rate (Strutzke *et al.,* 2018) panting and body temperature measurements (Ammer *et al.,* 2016) can be evaluated as indications of heat stress. Temperatures can be measured from various places in the body, e.g. rectum, vagina, peritoneum, ear, and reticulorumen (Ji *et al.,* 2017). Although rectal measurement is reliable, it has a low sampling rate, since it is done in a commercial way (Reuter *et al.*, 2010) manually and requires restraining the cow. Electronic, wireless measurements enable higher sampling frequency. Vaginal temperature is measured commercially (Burdick *et al.,* 2012) either manually or by an electronic logger inserted for a few days. The downside of the logger is the short period of time that it can remain in the vagina, and the impractical way in which the data is manually downloaded when the logger is removed. Now, the temperature of a cow can be measured in real-time by a bolus inserted into the rumen (reticulorumen). The boluses can measure the reticulorumen temperature as well as the pH. Wireless boluses are able to send data every ten minutes. The data can be stored in the cloud/computer. Depending on the battery life of the different bolus models, measurements can be taken for up to a year (Ammer *et al.*, 2016). The disadvantage of the bolus method is the location of the sensor in the reticulorumen, where it is affected by fermentation heat which is constantly 0.5 °C greater than the cow's core body temperature or by the cooling effect of the cow's drinking water (Bewley *et al.,* 2008). In order to address this issue and represent the cow's body temperature (vaginal) using reticulorumen temperature (bolus sensor), an algorithm was recently developed to remove drinking points from reticular temperature and correlate the reticulorumen fermentation temperature to the vaginal temperature (Goldshtein, 2018). Goldshtein algorithm quantifies the correlation between vaginal temperature and reticular temperature and enables reliable on-line continuous measurement of a cow's body temperature with the ruminal bolus.

To reduce heat stress, dairy barns located in arid or semi-arid climate zones use: shaded resting areas, shaded feeding and watering sites, ventilation, and evaporative cooling (Bucklin *et al.,* 1991, Ji *et al.*, 2017), using fans and water sprinklers (Flamenbaum *et al.*, 1986, Tresoldi *et al.*, 2018, 2019). Evaporative cooling is carried out several times a day, usually three to eight sessions a day, lasting 30-40 minutes each, at fixed hours, in cooling yards or along the feeding lanes (D'Emilio *et al.*, 2017). If the night temperature exceeds a certain level, a night cooling session is often added. In all of the studies reviewed, the cooling sessions were scheduled at constant times, regardless of the weather or conditions of the individual cow.

Hypotheses: A ruminal bolus sensor-based [SB] cooling method can be used to establish a cow cooling regime, which is more effective than a fixed, time-based [TB] cooling regime, and ensures that the average body temperature of a cow group does not exceed the heat stress threshold (39 °C). A cooling method based on the cow is more efficacious in reducing the cow's heat stress, functioning, output, and comfort than is one based on the cow's environment.

Therefore, the goal of this study is to describe the sensor-based method for scheduling the cooling sessions, and to validate this method on a research farm under severe heat conditions. Specifically, the goal of this study is develop (1) and test (2) a new cooling system based on the temperature of the cows, thus enabling the cooling sessions to be scheduled so as to closely respond to the cows' needs.

The innovative aspect

Using a bolus as a sensing device, cooling can be tailored to the cows' needs, thereby improving the cow's eating behaviour, milk production and comfort.

Material and methods

Concept

We set the body temperature heat stress threshold at 39 °C. Information about the cow's body temperature is collected and processed over a period of a week before a cooling decision is made. The critical periods during the day with the highest temperatures are recognised and cooling sessions are added or adjusted for these periods at the beginning of the following week. Hypothesis: correct cooling sessions can decrease the cow's temperature. Constant cooling sessions were compared with the other group, which was cooled by the sensor-based regime. The novelty of this method is using information obtained from low-cost commercially available sensors to improve the cow welfare and farm management by adapting the cooling schedule to the cows' needs and environmental conditions.

Statistical tools

The two cooling methods, TB and SB, were compared during the fifth through eighth weeks of the experiment with respect to the parameters: DMI, daily eating time, eating rate, visit frequency, visit length, visit size, diurnal eating distribution, daily lying, rumination time, milk yield of, 4% FCM and ECM, milk composition and efficiency in terms of RFI and ECM/DMI. All of the data were summarised for each day at the end of the experiment.

Data were analysed using a GLM F-test in JMPpro-13.0 software (SAS Institute Inc., 2016), with ANOVA repeated measures of cow as the subject. Tukey's HSD tests were used for comparisons of means between groups. Average DIM, parity and milk yield of the two cooling groups were kept similar during the experiment and calculated separately for the crossover. Covariance corrections were taken into account.

Reticulorumen data compared to vaginal data

RT data were compared to VT data using a model that was developed in a preliminary study conducted in the summer of 2016 (Goldshtein, 2018). The RT data, recorded every hour for 14 days, was analysed once a week and averaged for the aggregated group temperature, such that one aggregated hour represented the same hour of the previous 14 days for all cows. This data was used to evaluate the cow's heat stress using the RT to reflect the VT. During the first four weeks of the experiment (Figure 3), the times and durations of the cooling sessions were also changed according to the THI forecasted by the Agro meteorology unit in the Israeli Ministry of Agriculture. (Magrin *et al.*, 2017).

Results and discussion

During the fourth week, the length of time of the additional cooling sessions was modified, until the preferred cooling regime for the SB cows was reached. Under the preferred cooling regime achieved from the fourth week on, the animal temperature of the SB group did not reach the 39 °C heat-stress threshold (Figure 1). Figure 1 is the result of almost two months of trial and error until the situation in Figure 1 was reached.

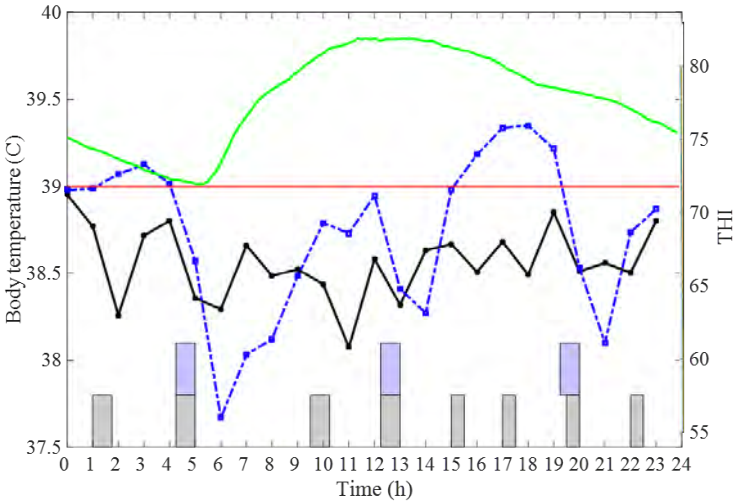

Figure 1. Weeks 5-8. Average body temperature (Y-axis) by hour (X-axis) during fifth to eighth weeks of the experimental period (when preferred cooling regime was achieved). Two treatments: sensor based (SB, black line, eight cooling sessions in gray columns), vs the time based (TB) group (blue line, three cooling sessions in blue columns), THI* is the green line; the predefined heat stress threshold (39.3 °C) is marked by a red horizontal line.

*THI — temperature-humidity index in this experiment ranged from 73–81 THI.

Minimal required number of boluses

A nearby commercial farm was equipped with 97 boluses in the cows with the same experimental setup. Using an extrapolation of the SD formula ($N=\sum(x-\bar{x})\ 2/SD$) we found that accurate monitoring of a group can be achieved with 30% of the group equipped with reticulorumen boluses (Figure 2).

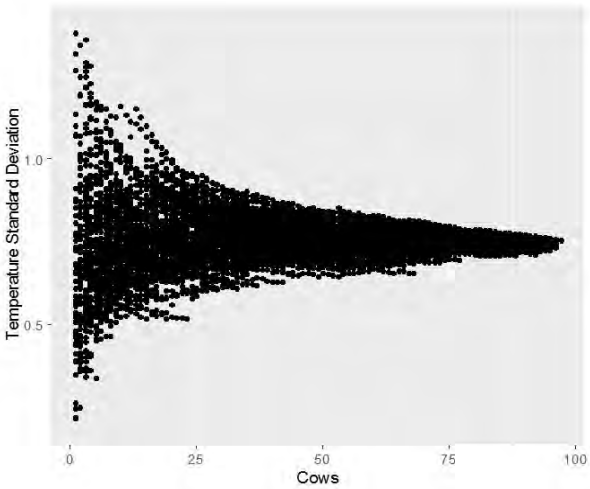

Figure 2. The minimum number of boluses needed for accurate sampling in one herd group. It can be seen that under 30% of the cows the sampling accuracy is insufficient due to high variance in temperatures

Although milk yield was similar in both groups (Table 1), under the preferred cooling regime (Figure 1), the SB group had higher milk protein (Table 1), higher milk fat and therefore, higher ECM and FCM 4% yields compared to the TB cows (Table 1).

Table 1. Production performance of the groups that experienced time-based (TB) cooling compared with the group that experienced sensor-based (SB) cooling

Measurement	TB	SB	*SEM*	*p*
N	15	15		
Milk, kg/d	44.7	44.7	0.37	0.99
Milk Fat, %	3.46	3.72	0.01	0.001
Milk Protein, %	3.15	3.26	0.01	0.001
Milk Lactose, %	4.89	4.83	0.01	0.001
ECM, kg/d	41.3	42.8	0.30	0.001
FCM 4%, kg/d	41.0	42.7	0.30	0.001
ECM/DMI	1.59	1.53	0.01	0.001
RFI, kg DM/d	1.03	1.03	0.01	0.93

ECM= energy corrected milk; FCM 4%= 4% Fat corrected milk; DMI = dry matter intake; RFI = residual feed intake [actual DMI – predicted DMI, (NRC, 2001)]

Conclusions

The sensor-based cooling regime maintained the cow's body temperature under a predefined heat stress threshold of 39 °C. The cows under 39 °C showed higher DMI consumption (28.4 vs 26.4), higher ECM (42.8 vs 41.3) and FCM productions levels (42.7 vs 41), and were more comfortable in terms of rumination.

Adapting the frequency, timing and duration of the evaporative cooling sessions to the real-time reticulorumen temperature might be a practical tool for farmers in semi-arid zones. Elsewhere, in extreme climate events, this sensor-based method may enable the dairy farmer to cope with the effect of climate change and ease the heat stress of cows.

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References

Ammer, S., C. Lambertz, and M. Gauly. (2016). Comparison of different measuring methods for body temperature in lactating cows under different climatic conditions. *Journal of Dairy Research*, 83(2): 165–172.

Bewley, J., M. Grott, M. Einstein, and M. Schutz. (2008). Impact of intake water temperatures on reticular temperatures of lactating dairy cows. *Journal of Dairy Science*, 91(10): 3880–3887.

Bucklin, R., L. Turner, D. Beede, D. Bray, and R. Hemken. (1991). Methods to relieve heat stress for dairy cows in hot, humid climates. *Applied Engineering in Agriculture*, 7(2): 241–247.

Burdick, N., J. Carroll, J. Dailey, R. Randel, S. Falkenberg, and T. Schmidt. (2012). Development of a self-contained, indwelling vaginal temperature probe for use in cattle research. *Journal of Thermal Biology*, 37(4): 339–343.

D'Emilio, A., S.M. Porto, G. Cascone, M. Bella, and M. Gulino. (2017). Mitigating heat stress of dairy cows bred in a free-stall barn by sprinkler systems coupled with forced ventilation. *Journal of Agricultural Engineering*, 48(4): 190–195.

Ferreira, F., R. Gennari, G. Dahl, and A. De Vries. (2016). Economic feasibility of cooling dry cows across the United States. *Journal of Dairy Science*, 99(12): 9931–9941.

Flamenbaum, I., D. Wolfenson, M. Mamen, and A. Berman. (1986). Cooling dairy cattle by a combination of sprinkling and forced ventilation and its implementation in the shelter system. *Journal of Dairy Science*, 69(12): 3140–3147.

Goldshtein, S. (2018). Heat stress prediction in dairy cows. in Department of Industrial Engineering & Management. Vol. Master Science. Ben- Gurion University of the Negev, Faculty of Engineering Sciences.

Honig, H., J. Miron, H. Lehrer, S. Jackoby, M. Zachut, A. Zinou, Y. Portnick, and U. Moallem. (2012). Performance and welfare of high-yielding dairy cows subjected to 5 or 8 cooling sessions daily under hot and humid climate. *Journal of Dairy Science*, 95(7): 3736–3742.

Ji, B., T. Banhazi, C. Wang, and B. Li. (2017). PLF technologies: model development for solving heat stress problems on dairy farms.

Magrin, L., M. Brscic, I. Lora, C. Rumor, L. Tondello, G. Cozzi, and F. Gottardo. (2017). Effect of a ceiling fan ventilation system on finishing young bulls' health, behaviour and growth performance. *Animal*, 11(6): 1084–1092.

Mellado, M., L.M. Lara, F.G. Veliz, M.Á. d. Santiago, L. Avendaño-Reyes, C. Meza-Herrera, and J.E. Garcia. (2015). Conception rate of artificially inseminated Holstein cows affected by cloudy vaginal mucus, under intense heat conditions. *Pesquisa Agropecuária Brasileira*, 50(6): 492–498.

Piccione, G., G. Caola, and R. Refinetti. (2003). Daily and estrous rhythmicity of body temperature in domestic cattle. *BMC Physiology*, 3(1): 7.

Polsky, L. and M.A. von Keyserlingk. (2017). Invited review: Effects of heat stress on dairy cattle welfare. *Journal of Dairy Science*, 100(11): 8645–8657.

Prendiville, D.J., J. Lowe, B. Earley, C. Spahr, and P. Kettlewell. (2002). Radiotelemetry systems for measuring body temperature. Teagasc.

Reuter, R., J. Carroll, L. Hulbert, J. Dailey, and M. Galyean. (2010). Development of a self-contained, indwelling rectal temperature probe for cattle research. *Journal of Animal Science*, 88(10): 3291–3295.

Schueller, L.K., O. Burfeind, and W. Heuwieser. (2014). Impact of heat stress on conception rate of dairy cows in the moderate climate considering different temperature-humidity index thresholds, periods relative to breeding, and heat load indices. *Theriogenology*, 81(8): 1050–1057.

St-Pierre, N., B. Cobanov, and G. Schnitkey. (2003). Economic losses from heat stress by US livestock industries1. *Journal of Dairy Science*, 86: E52-E77.

Strutzke, S., D. Fiske, G. Hoffmann, C. Ammon, W. Heuwieser, and T. Amon. (2018). Development of a noninvasive respiration rate sensor for cattle. *Journal of Dairy Science*.

Stull, C., L.M. Messam, C. Collar, N. Peterson, A. Castillo, B. Reed, K. Andersen, and W. VerBoort. (2008). Precipitation and temperature effects on mortality and lactation parameters of dairy cattle in California. *Journal of Dairy Science* 91(12):4579–4591.

Tresoldi, G., K.E. Schütz, and C.B. Tucker. (2018). Cooling cows with sprinklers: Timing strategy affects physiological responses to heat load. *Journal of Dairy Science* 101(12):11237–11246.

Tresoldi, G., K.E. Schütz, and C.B. Tucker. (2019). Cooling cows with sprinklers: Effects of soaker flow rate and timing on behavioral and physiological responses to heat load and production. *Journal of Dairy Science*.

West, J. (2003). Effects of heat-stress on production in dairy cattle. *Journal of Dairy Science* 86(6):2131–2144.

Poster Session

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Comparison of data driven mastitis detection methods

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Abstract

The aim of this study is to compare the performances of different data driven methods for their ability in early detection of clinical mastitis. Many scientific papers on data driven methods for early mastitis detection have been published in the last decade. The performances vary greatly as well as the data used, the applied time window, and the gold standard definition. To compare the performances of these data driven methods, this study applied various data driven methods including time series filtering and classification methods (i.e. Naïve Bayesian networks and Random Forest) under similar conditions. Forecast errors and filtered means of the time series models were used to distinguish mastitis cases from non-cases. Moreover, we focused solely on electrical conductivity (EC) measures of milk to detect clinical mastitis. Data for this study were provided by Lely Industries and originate from 57 farms in six different European countries with a total of 1,094,780 cow milkings with EC measurements at quarter milk level. It is hypothesised that the performances with respect to mastitis detection will differ substantially between the different methods, and that the ranking of methods is not consistent across different datasets. Despite this, our preliminary results suggest that the performances of Naïve Bayesian networks and Random Forest do not vary much. The various filtering methods also present similar results. Although our naive approach of data handling allows us to compare different methods, we expect that each method in itself have the potential to improve when other (historical) variables than just EC are included.

Keywords: mastitis, classification, transformation, filtering, EC

Introduction

Sensors generate a large amount of data but as such do not provide any information on which decisions can or should be taken. With the development of mastitis sensor systems, an increasing number of scientific papers on early mastitis detection are being published (Hogeveen *et al.*, 2010), and various data driven methods are applied to translate sensor data into useful information for mastitis detection (Dominiak and Kristensen, 2017). Not only do these publications report a wide range of applied methods, but they also use a wide variety of gold standards for mastitis, time windows for detection, and the selection of sensor data. This makes the studies difficult, if not impossible, to compare.

Timely detection of mastitis is of interest from an animal health and welfare perspective, but also plays an important economic role. Milk electrical conductivity (EC) is the most commonly used sensor data to detect clinical mastitis (De Mol and Ouweltjes, 2001; Khatun *et al.,* 2017). Other sensor data like milk colour, somatic cell count, and milk yield have been used to classify abnormal milk, often caused by clinical mastitis (Ebrahimie *et al.*, 2018). For the early detection of mastitis, alerts need to be generated. This is commonly achieved by applying methods that can produce an alert when the measured sensor data (that are considered a proxy for cow health status) deviates from the expected measurements (being a proxy for a normal, i.e. healthy status).

In the search for a perfect alert (that is, all mastitis cases receive an alert in time with 100% positive predictive value) a combination of different data driven methods have been used. Roughly we can distinguish three method families: filter methods, transformation methods, and classification methods. Filtering is a pre-processing method that defines, detects and corrects errors of raw sensor data to minimize the impact of these errors on the succeeding subsequent analyses. Filtering methods are used to remove noise from time series measurements and thus highlight the underlying trends from a signal and estimate the true underlying value. Transformation methods are also referred to as a pre-processing step which makes input data more amendable by changing a range of numbers from one representation to another. Filtering or transformation methods to the data can result in more suitable parameters to be used for classification. Classification methods are used to convert the sensor data into and alert for mastitis detection.

The accuracy of the classification methods are evaluated by calculating the specificity (Sp) and sensitivity (Se), which are statistical measures of a binary classification test. Studies report various performance levels, ranging between 69 - 99% for Sp and 32 -100% for Se (Hogeveen *et al.*, 2010, Dominiak and Kristensen, 2017). Most of these studies used a combination of sensor and non-sensor data. When based solely on sensor data, the detection of all clinical mastitis cases, with a manageable number of false positive attentions, remains highly challenging.

Improving the performances of classification methods can be achieved by combining different data sources and changing the time-window. The objective of this paper is to evaluate the performances of several data driven methods for the early detection of clinical mastitis under similar conditions (i.e. data input, data selection criteria, time-window and gold standard). With this paper we want to strengthen the knowledge on the performance of different methods in relation to mastitis detection.

Material and methods

Data management

For this study we used sensor data on EC and somatic cell count (SCC), which had been automatically recorded using Lely milking robots, along with information to identify the individual cow and the herd it came from. Lely Industries (Maassluis, the Netherlands) provided these data.

We included a total of 296,501 records from 344 individual cows, encompassing 57 farms in four different European countries. Each individual cow was only represented with a single lactation. The included records were all made on days in milk (DIM) between 4 and 305. Only cows where SCC had been recorded at least once per week during this period were included in this study.

A SCC above 150,000 cells/mL was considered elevated for primiparous cows, and 250,000 cells/mL was considered elevated for multiparous cows, in accordance with Dutch standard practice based on the paper by Schepers *et al.* (1997). A cow was defined as having a mastitis event (ME) based on Kamphuis *et al.* (2016): at a given observation time if at least two of the three most recent milkings showed elevated SCC. A single mastitis event was not limited to three consecutive milkings, but could continue as long as SCC is elevated. The ME start at the milking where SCC is elevated for the first time, and ends at the last observation of elevated SCC, followed by four observation without SCC elevation.

From the 344 cows, 19 cows did not experience any ME. The cows, which did experience mastitis at least once (N = 325), were divided into a training set for training different classification methods, and a test set for assessing the performance of these trained

models on independent data. This division was based on farm, where 2/3 of the farms were randomly selected to be used in the training set, and the remaining 1/3 were used as the test set. This division by farm was done to ensure independence between training and test data.

Time series filtering

For this study, we implemented a total of four different time series filtering methods, which are commonly used in the scientific literature relating to precision livestock farming. These filtering methods were optimized on the 19 cows without any ME in their lactation. The filtering methods were, in order of increasing complexity: 1) a moving average (MA), 2) an exponentially weighted moving average (EWMA), 3) a univariate dynamic linear model (DLM), and 4) a multivariate DLM. These were all implemented in R (R Core Team, 2017). Each of the filtering methods was optimised by finding the value of the relevant variables (see below), which minimised the root of the mean squared errors (RMSE) when applied to the filtering optimisation data.

Moving Average (MA)

At each time step, the filtered value, z_t, is defined as the simple mean of the *n* most recently observed values, with n being a predefined integer value called the "window length". The forecast for the observation at a given time t is given as the filtered value, z_{t-1}), at time t-1. The forecast variance is estimated as

$$\sigma_{zt}^2 \approx \frac{\sigma^2}{n} \tag{1}$$

where σ^2 is the variance of the observed values and k_t is the window length. The MA was optimised for this study by trying values of *n* between 1–10 by steps of 1.

Exponentially weighted moving average (EWMA)

At each time step, the filtered value is defined according to the following equation:

$$z_t = \lambda \cdot k_t + (1-\lambda) \cdot z_{t-1} \tag{2}$$

where λ is a scale factor which can take values between 0–1, and k_t is the observed value at time *t*. The forecast for the observation at a given time *t* is given as the filtered value, z_{t-1}, at time *t*-1. The forecast variance is estimated as

$$\sigma_{zt}^2 \approx \sigma^2 \cdot \left(\frac{\lambda}{2-\lambda}\right) \tag{3}$$

where σ^2 is the variance of the observed values. The EWMA was optimised by trying values of λ between 0–1 by steps of 0.01.

The univariate and multivariate dynamic linear model (DLM)

For this study, we implemented first-order univariate and multivariate DLMs without systematic growth components. At each time step, the EC values are filtered using the Kalman filter, as described in detail by West & Harrison (1997). The filtered values of one (univariate) or four (multivariate) EC values at time step *t* are defined by the system equation:

$$\theta_t = \theta_{t-1} + w_t \tag{4}$$

where θ_t is the parameter vector, and the error term is defined as $w_t \approx N(\underline{0}, \mathbf{W})$ with $\mathbf{W}$ being the systematic co-variance matrix. In our implementation, $\mathbf{W}$ was estimated continuously during the Kalman filtering by means of a discount factor, δ, which can take values between 0–1 (West & Harrison, 1997). The discount factor was optimised separately for the univariate and multivariate DLM by trying values of δ between 0–1 by steps of 0.01.

Forecasts of the expected EC values at time step *t* are made according to the observation equation:

$$\mathbf{Y}_t = \theta_t + \boldsymbol{v}_t \tag{5}$$

where Y_t is the observation vector with a length of 1 for univariate model and 4 for the multivariate model. The error term is defined as $v_t \approx N(\underline{O},V)$ with V being the observational co-variance matrix, with the dimensions 1×1 for the univariate model and 4×4 for the multivariate model. The values of **V** were found using the expectation maximization algorithm, as described in detail by West & Harrison (1997.

At each observation time, the forecast errors were calculated according to equation 6.

$$\boldsymbol{e}_t = \mathbf{Y}_t - \theta_t \tag{6}$$

Given the forecast errors for each observation time, the parameter vector values are updated using the Kalman filter (West and Harrison, 1997). The forecast variance-covariance matrix is estimated as part of the Kalman filtering (West and Harrison, 1997). The dimensions of this matrix is 1×1 for the univariate DLM and 4×4 for the multivariate DLM.

Standardization

For the MA, EWMA, and the univariate DLM, the forecast errors were standardised using the forecast variance, according to equation 7.

$$u_t = \frac{e_t}{\sqrt{\sigma_{z_t}^2}} \tag{7}$$

For the multivariate DLM, the forecast errors were standardised in the same way, except using only the diagonal values of the forecast variance - covariance matrix.

Observation classification

The four optimised time series filtering models were applied to the of EC observations in the original training set, resulting in four different new training sets. These new training sets contained 12 predictor variables per observation, namely the unfiltered EC values, the filtered EC values, and the standardised forecast errors for each of the four quarters. Based on these predictor variables, different machine learning methods were trained to classify the individual milkings as being from a mastitis positive or negative milking, as described below.

Random Forest and Bayesian Network

We set up an experiment in the machine learning and data mining tool WEKA (Witten and Frank, 2005) to be used for each of the four training datasets. In the experiment, two main algorithms were selected, namely Random Forest (RF) and Bayesian network (BN). Each of these two algorithms were set up with different combinations of parameter settings resulting in a total of 31 different model configurations to be evaluated (for details, see Tables 1 and 2). Each of these model configuration was evaluated with 5-fold cross validation on each of the training datasets. Mastitis (yes/no) was used as the categorical output variable. No further pre-processing was performed.

Table 1. Overview of the parameter settings used with the random forest method

Main algorithm	Parameter settings		Abbreviation
	No. of trees	Seed	
Random Forest	3	1 - 5	RF031 - RF035
	10	1 - 5	RF101 - RF105
	25	1 - 5	RF251 - RF255

Table 2. Overview of the parameter settings used with the Bayesian network method

Main algorithm	Parameter settings		Abbreviation
	Search algorithm	Max number of parents	
Bayesian network	Local	1 - 5	BNL1 - BNL5
	TAN	N/A	BNTan
	Tabu	1 - 5	BNT1 - BNT5
	Hill Climber	1 - 5	BNH1 - BNH5

Each of the 31 model configurations produced a probability of having mastitis for each record in each of the four training sets. If this probability was > 0.5, the final output was categorised as 1 (mastitis predicted), and else the final output was categorised as 0 (no mastitis predicted). These predictions were compared with the true status of each record to assess true positive (TP), false negative (FN), true negative (TN), and false positive (FP) predictions per records. Per model, threshold settings were changed such that Se of finding ME was ~60% at milking level. At that level, FAR1000 was reported. This process was repeated for each of the four training sets using Weka experimenter. Based on these performance parameters, one model configuration for each of the two main algorithms was selected for further analysis.

Model testing

The selected configurations of the three classification models (RF, BN, and Sewhart control chart) were applied to each the four related test dataset, probabilities were produced for each records, and these probability were transformed into a 0/1 output, depending on the threshold. We then applied the time-window proposed by Kamphuis *et al.* (2016) to compute TP and FN alerts for each ME. This time-window assumes that an alert from any mastitis detection model can be expected from up to two milkings prior to the first milking of an ME, and then for the entire duration of an ME. Alerts earlier than the two milkings prior to the start of an ME, or after the last milking of an ME are thus considered as a FP alert. Subsequently, each ME is counted as either being missed (one FN alert) or as one correctly identified ME (one TP alert), although more than one milking within a ME could have received a TP alert. For milkings not belonging to an ME, which thus had a true no-mastitis status, no time-window was used. This means that each no-mastitis milking receiving an alert by the model were counted as FP, and each no-mastitis milking not receiving an alert were counted as TN. The TP and FN were used to compute Se, while the TN and FP alerts were used to compute the number of alerts per 1,000 milkings (FAR1000).

Per model, threshold settings were adjusted such that Se of finding ME was ~60%. At that level, FAR1000 was reported. Furthermore, the specificities and error rates were calculated as secondary measures of performance for the different classification methods.

Results and discussion

The aim of this study was to compare the performances of different combinations of filtering and classification methods under standardised conditions. The ability of human milkers to detect clinical mastitis has been reported with an average sensitivity of 80%, although this number in practice depends on the skill of the milker and the severity of the mastitis case (Hillerton and Kliem, 2002). For comparison, the scientific literature reports an average sensitivity of 60% when using automated detection systems in the field (Hogeveen *et al.*, 2010). For this reason the sensitivity in this study was fixed at 60%, and thus the threshold for which outputs would count as alarms was optimised for each classification methods. Table 3 summarises the performances achieved with the various method combinations.

Table 3. Preliminary results of the data driven methods

Classification method	Filtering method[1]	Sensitivity (%)	Specificity (%)	FAR1000[2]	Error rate (%)
Random forest	MA	59.9	74.8	217.7	95.6
	EWMA	60.8	73.7	227.6	95.8
	DLM uni	60.2	75.2	214.2	95.6
	DLM multi	60.7	74.1	224.2	95.7
Bayesian network	MA	60.5	73.0	233.3	96.0
	EWMA	60.3	73.8	226.5	95.9
	DLM uni	59.4	71.8	234.7	96.1
	DLM multi	59.9	74.1	224.5	95.8

[1]Filtering methods: moving average (MA), exponentially weighted moving average (EWMA), univariate dynamic linear model (DLM uni), and multivariate DLM (DLM multi); [2]Number of alerts per 1,000 milkings

The results obtained for the test data were comparable to the results for the training data, which argues for the validity of the model and suggests that the model does not over-fit to the data. This may indicate that the model is generally applicable. Table 3 shows the detection performance of the classification methods using different filtered datasets. The Sp is ranging between 71–75%, with an Se of 60%. The performances of the models in this study are lower compared to findings from the literature. This, however, was expected since we do not search for the best possible model, but rather seek to compare different filtering and classification methods more objectively. The specificity rate obtained with the classification seem rather similar. The error rates were high, ranging between 95–96%. Since there are many more days with a healthy stage than days of mastitis, it causes a greater likelihood for FP to arise, which has an impact on the error rate. The results of the filtering methods showed similar results.

The different filtering methods do not vary a lot in Sp, FAR1000 and error rate. The number of CM episodes indicated with Random Forest suggest to be higher than for the Bayesian Network. The FAR1000, however, indicates that more alert are generated with Bayesian Network than for the Random Forest. Despite some differences, the results suggest that the performances of these two classification methods do not vary a lot. In the next step of this study we will look also at the relative more straightforward methods like a Shewart

Control chart. We hypothesise that the performances of such methods are less compared to the more advanced classification methods. Besides, we know that the Shewart Control works fine with continuous variables like EC, but utilizing the categorical variables (e.g. parity), this simple method will quickly become much more complicated to implement.

The results of this study should be interpreted as a relative comparison. According to Hamann and Zecconi (1998), using EC in milk as a mastitis is a good indicator. However, the performances of the classification methods are expected to be improved when including other variables, like milk yield and SCC. Additionally, including historic data (from e.g. previous milkings) are also expected to improve the detection performances. The naïve approach we used in this study was necessary to enable a fair comparison between the performances of classification and filtering methods.

Conclusions

This study aimed to evaluate performances of several data driven methods for the early detection of mastitis, using similar conditions (i.e. data input, data selection criteria, time-window and gold standard). So far, there is an indication that our naive approach of data handling results in no clear distinction in performance between the different methods.

References

De Mol, R.M., and Ouweltjes, W (2001). Detection model for mastitis in cows milked in an automatic milking system. *Preventive Veterinary Medicine,* 49: 71–82.

Dominiak, K.N., and Kristensen, A.R. (2017). Prioritizing alarms from sensor-based detection models in livestock production – a review on model performance and alarm reducing methods. *Computer Electronics in Agriculture,* 133: 46–67.

Ebrahimie, E., Ebrahimi, F., Ebrahimi, M., Tomlinson, S., and Petrovski, K.R. (2018). Hierarchical pattern recognition in milking parameters predicts mastitis prevalence. *Computers and Electronics in Agriculture,* 147: 6–11.

Hogeveen, H., Kamphuis, C., Steeneveld, W., and Mollenhorst, H. (2010). Sensors and Clinical Mastitis—The Quest for the Perfect Alert. *Sensors*, 10: 7991–8009.

Hillerton, J.E., Kliem, K.E. (2002). Effective treatment of Streptococcus uberis clinical mastitis to minimize the use of antibiotics. *Journal of Dairy Sciences,* 85: 1009–1014.

Kamphuis, C., Dela Rue, B.T., and Eastwood, C.R. (2016). Field validation of protocols developed to evaluate in-line mastitis detection systems. *Journal of Dairy Sciences,* 99: 1619–1631.

Khatun, M., Clark, C.E.F, Lyons, N.A., Thomson, P.C., Kerrisk, K.L., and García, S.C. (2017). Early detection of clinical mastitis from electrical conductivity data in an automatic milking system. *Animal Production Science*, 57: 1226–1232.

Schepers, A.J., T.J.G.M. Lam, Y.H. Schukken, J.B.M. Wilmink, and W.J.A. Hanekamp. (1997). Estimation of Variance Components for Somatic Cell Counts to Determine Thresholds for Uninfected Quarters. *Journal of D*airy Science, 80: 1833–1840.

West, M., and Harrison, J. (1997). Bayesian Forecasting and Dynamic Models, 2nd ed. Springer, New York, USA.

Witten, I.H., and Frank, E. (2005). *Data Mining; Practical Machine Learning Tools and Techniques.* Morgan Kaufmann Publishers, San Francisco.

Activity analysis and lameness detection in fattening pigs using a UHF-RFID system

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Abstract

The objective of this paper is to monitor the behaviour of fattening pigs with an ultra-high frequency radio frequency identification system (UHF-RFID) and to detect lameness with this data. The RFID system can identify and register the pigs' visits at the trough, the drinkers and a playing device at all times. With this system, it is possible to monitor a large part of the daily behaviour of pigs on group level but also individual level. Because a strong connection of behaviour to health issues is presumed, different approaches to detect illnesses, focusing on lameness, were tested. Along with the daily duration at the different hotspots, an approach to regard the first visiting time of a hotspot was examined. Results show changings in behaviour of some pigs with lameness detection, but also the difficulties due to the high intra- and inter-animal variability of the behaviour and the interaction of different parameters.

Keywords: UHF-RFID, behaviour, activity, fattening pigs, lameness detection

Introduction

Health monitoring on the level of the individual animal has become a growing challenge in modern pig husbandry due to increasing herd sizes. Additionally, the level of interest in animal welfare, product traceability and transparency of production methods on the consumer side is rising. Hence, systems for automatic health and activity monitoring of individual pigs are demanded and would support the farmer in management issues. An individual identification of the animals is the basis of all monitoring applications (Adrion *et al.*, 2015). By using RFID (Radio Frequency Identification) for electronic animal identification, the pigs' visits at different hotspots in the pen (e.g. at the trough) can be registered (Brown-Brandl *et al.*, 2013; Maselyne *et al.*, 2014; Maselyne *et al.*, 2016a). With UHF-RFID technology (ultra-high frequency RFID) a simultaneous identification of several pigs is possible without separating the individual animals and with a relatively high reading range (Adrion *et al.*, 2015; Barge *et al.*, 2013).

The recording of the duration and frequency of visits at a specific hotspot can be an indicator for the behaviour of animals. For example, a pig detected at the trough for a specific time was most likely feeding. Due to the strong connection of behaviour to different kinds of illnesses, analysing a pig's behaviour may lead to conclusions on the animal's health (Matthews *et al.*, 2016; Weary *et al.*, 2009).

The aim of this research is to develop a health and activity monitoring system based on UHF-RFID by analysing the visiting events of growing-finishing pigs at the trough, the drinkers and a playing device. In this article, different approaches to distinguish sick animals from healthy ones, focusing on lameness detection, are pointed out. The focus lies on the detection of lame pigs by analysing visit times and durations at different hotspots on an individual level.

Material and methods

Research barn, animals and technical equipment

The study was carried out in a conventional fattening pig barn at the Agricultural Sciences Experimental Station of the University of Hohenheim, Germany, in four fattening periods over a time of about two years altogether (August 2016 to November 2018). The experimental procedures were approved by the regional authorities in Baden-Württemberg, Germany, and were carried out in accordance with EU Directive 2010/63/EU for animal experiments. Each pen was equipped with three nipple drinkers in every pen as well as a metal trough (1.50 m × 0.37 m) with a sensor-controlled liquid feeding system. The feeding was distributed over six feeding times, starting at 6 am and ending with the last feeding at 10 pm in the evening. In each fattening period, four mixed-gender groups of growing-finishing pigs (25 per pen, 100 in total) were tagged with UHF-RFID transponder ear tags. The ear tags were developed within a previous research project (Hammer, 2017; Adrion, 2018). The transponders were equipped with an Impinj Monza 4® chip and had a PIF antenna design (Planar Inverted f-Shaped Antenna; Adrion *et al.*, 2015). They were grouted into a flexible plastic ear tag (Primaflex®, Caisley International GmbH, Bocholt, Germany). The pigs had an average weight of about 30 kg at the beginning of the trial and were fed to a total weight of about 120 kg.

The hotspots for feeding, drinking and playing in the pens were equipped with UHF antennas. Along the length of the trough, a cable antenna with an active length of 2 m was installed in a plastic pipe (Locfield®, Cavea Identification GmbH, Olching, Germany). Cable antennas in plastic pipes were also mounted vertically to the right of the nipple drinkers (Locfield® with 0.35 m active length, Cavea Identification GmbH). At the playing device ("Porky Play", Zimmermann Stalltechnik GmbH, Oberessendorf, Germany), a mid-range antenna was located at the top (MIRA-100, Kathrein Sachsen GmbH, Stephanskirchen, Germany).

The readers used were functional models (deister electronic GmbH, agrident GmbH, Barsinghausen, Germany) with a multiplexer for four antennae, a maximum output power of 29 dBm and an operating frequency of 865.7 MHz. The communication between reader and transponder followed EPC class 1, generation 2, specifications defined by ISO 18000 6C. Each antenna was switched on for 250 ms per second in the multiplexing process. The transponder ear tags could be read by the antennae approximately once per second. Simultaneous reading of multiple transponders was enabled by using anti-collision procedures, which allow the reader to coordinate the points in time at which the transponders send their data.

The data collection within the four fattening periods lasted between 15–19 weeks. During this time, the temperature and humidity inside the compartments were continuously logged by data loggers every 10 minutes (testo 175H1, Testo AG Lenzkirch, Germany). Twice a week, the health status of the individual pigs was observed including lameness, skin lesions (number of scratches) and soiling (scale from 0–3), tail lesions (scale from 0–2), diarrhoea (binary scale), coughing (number of coughing bouts per pig) and sneezing (number per pen). Additionally, the individual weights of the pigs were measured every four weeks. Lameness was of particular interest for this analysis. The severity of lameness was determined by a 0–3 scale, the Locomotion Score (LS) (ZINPRO Feet First®). A score of 0 was assigned to pigs without any sings of lameness. A locomotion score of 1 is described by visible signs of lameness, which does not affect the pigs to any great extent. The pig can still move around easily and the lameness would normally not be detected or treated. A locomotion score of two was assigned to pigs that show lameness in one or more limbs as well as compensatory behaviours such as dipping the head or arching the back, whereas

a score of three was assigned to pigs with a strong reluctance to walk and bear weight on one or more legs. Due to a preceding validation phase in fattening Period 1, the health observation started about 10 days later than in the other fattening periods, which results in a maximum of 30 health observation days for Period 1, 34 days for Period 2, 36 for Period 3 and a maximum of 37 health observation days in Period 4. Not all pigs stayed in the barn over the complete trial time. Due to differences in growing, some pigs had a shorter period of fattening than others. Furthermore, 19 out of 400 pigs needed to be removed into another barn because of severe health conditions (e.g. severe lameness, tail biting). This results in a total number of 2,505 health observations (health observation days × pigs inside the test barn) in fattening Period 1; 2,845 health observations in Period 2; 3,073 in fattening Period 3 and 3,255 health observations in fattening Period 4. On the days between the observation days, the pigs with health issues were observed by the animal caretakers. These data are not included in the current analysis for reasons of comparability.

Data analysis

The UHF-RFID system consisting of UHF ear tags, UHF antennae, readers and a monitoring software (Phenobyte GmbH, Ludwigsburg, Germany), which recorded occurring RFID registrations, collected data constantly throughout the fattening periods. The software aggregated the RFID registrations using a minimum duration and a bout criterion to create visits out of the raw data. These visits were used for calculating the daily visiting time of each pig at a hotspot to monitor the general behaviour of the pigs and to determine whether there were differences between the three fattening periods. To specify the most appropriate aggregation for each hotspot, various combinations of minimum durations (0 s, 1 s, 3 s, 5 s) and bout criteria (20 s, 30 s, 40 s, 50 s, 60 s) were tested and compared to the results of video observation in terms of sensitivity and precision (positive predictive value) according to common definitions (e.g. Maselyne *et al.*, 2016b; Adrion *et al.*, 2018). The video observation was carried out with ten focal pigs on two days with at least 11.5 hours of observation time per hotspot and day, resulting in a total observation time between 23.5–28 hours per hotspot. For the drinkers and the playing device, the events when pigs were lying inside the hotspot area without drinking or playing were excluded from the analysis. The selected combination was a minimum duration of 1 s and a bout criterion of 60 s at the trough, 0 s and 50 s at the drinkers and a minimum duration of 3 s with a 40 s bout criterion at the playing device. The sensitivity at the trough was approx. 85%, the precision approx. 64%. At the drinkers, the sensitivity and the precision were both approx. 60% and at the playing device, the sensitivity was approx. 81%, the precision approx. 54%.

For the calculation of the daily durations at the different hotspots, the aggregated events (with individual minimum duration and bout criterion for each hotspot) were used.

For the calculation of the first visit at the trough, the RFIDreadings at this hotspot were examined after the first feeding time at 6 am. Readings were counted as a visit, only if the minimum duration was at least 60 s with a bout criterion of 30 s.

Results and discussion

During the trial period, signs of lameness were the most frequently observed health issue. Other issues like coughing or diarrhoea were only detected between three and 20 times within a fattening period and were not consistent. Thus, the number of these events was not sufficient for creation of a prediction model and they were considered negligible. Furthermore, severe health problems like pneumonia did not occur during any of the three fattening periods. For this reason, the analysis in this study focuses only on lameness issues. Pigs with a severe lameness and a strong reluctance to walk (LS 3) were often treated or even removed from the pen, and thus from the trial. Sometimes a treatment

was considered as not expedient by the caretakers because of unclear symptoms; instead the pigs were observed intensely.

In fattening Period 1, there were only 10 pigs that showed a locomotion score of two or higher on at least 15% of the health observation days they were in the trial barn. In fattening Period 2, there were 32 and in fattening Period 3 there were 30 pigs with this condition, out of which one was in the barn for only 11 health observation days. In fattening Period 4 there were 52 pigs in total that showed a locomotion score of two or higher on at least 15% of the health observation days. The reason for this is unknown, but the prevalence for lameness in this barn is relatively high. This might be indicated by the short trough which results in low animal:feeding place ratio and by the fully slatted flooring. An optimisation of the research barn is aimed at for future studies. There were 26 pigs in fattening Period 1 that showed no sign of lameness during the complete period. In fattening Period 2 and 3, there were only five such pigs each, out of which one pig in the fattening Period 2 was only in the barn for four health observation days. In fattening Period 4 there was not a single pig that showed no sign of lameness throughout the complete fattening period and only five pigs with a maximum lameness score of 1. This means, 95 out of 100 pigs in fattening Period 4 had a lameness score of two or higher on at least one of the 37 health observation days.

Daily mean values

The overall mean of the visiting time of all pigs at the trough throughout all days over all three fattening periods was 54.9 ± 31.6 minutes (mean value ± standard deviation). The mean visiting duration at the drinkers was 9.1 ± 11.2 min and at the playing device 38.2 ± 29.0 min. In Table 1, the average daily mean values are grouped by fattening period. The mean values showed no noticeable difference between the different trial periods at the trough and the drinkers. Only the visiting time at the playing device was a little shorter in the third fattening period. The standard deviations were relatively high compared to the mean values themselves, which indicates a high variance in the dataset. Table 2 shows the pigs with the lowest and the highest average daily visiting time at the different hotspots grouped by fattening period. The minimum and maximum of the average time a pig spent at a hotspot also shows the high variability between the pigs as individuals. Because of this high variability, regarding mean values only is insufficient for any kind of illness detection and far more detailed analyses are necessary.

Table 1. Mean value (mv) and standard deviation (sd) of daily visiting time of all 400 pigs at the hotspots over the four different fattening periods

	Trough mv ± sd [min]	**Drinkers mv ± sd [min]**	**Playing device mv ± sd [min]**
Fattening period 1	55.3 ± 27.6	8.4 ± 9.2	41.0 ± 30.3
Fattening period 2	60.1 ± 35.3	5.9 ± 5.3	42.7 ± 32.0
Fattening period 3	51.9 ± 28.8	9.4 ± 12.0	30.5 ± 23.1
Fattening period 4	52.6 ± 32.6	12.6 ± 14.4	38.9 ± 28.6

Table 2. Pigs with the lowest and the highest average daily visiting time at the trough, the drinkers and the playing device

		Trough		Drinkers		Playing device	
		Duration [min]	Pig No.	Duration [min]	Pig No.	Duration [min]	Pig No.
Fattening period 1	Min.	28.9	53	2.6	42	7.7	42
	Max.	123.2	94	21.2	86	97.4	54
Fattening period 2	Min.	20.9	171	2.3	110	14.3	109
	Max.	164.5	118	18.3	176	103.8	142
Fattening period 3	Min.	20.9	267	2.1	211	13.9	296
	Max.	141.7	218	38.4	268	76.0	295
Fattening period 4	Min.	17.5	371	3.4	314	8.8	357
	Max.	131.3	308	37.6	369	75.2	395

Development of daily visiting time at the hotspots

Alterations of the daily visiting time or changings in the time of the first visit of a specific hotspot over the whole period of the trial could indicate health issues. Figure 1 shows the average visiting time at the hotspots trough, drinkers and playing device over all four fattening periods, divided by three fattening stages (Day 1 - 30, Day 31 - 60 and Day 61 - 90). The x-axis starts with 6 am because the values before that time are much lower (maximum about 30 min). At the trough, the feeding times during the day are clearly visible in the data, but there are also visits between those times. Those can be explained by leftovers in the trough and foraging behaviour of the pigs. The drinkers are mostly frequented during the afternoon times. The visiting time at the drinkers is generally low, which can be explained by the liquid feeding system and thus the low need for additional water intake. The three different fattening stages have differences in the visiting times at the trough and the playing device. While the pigs in the early fattening stage (1 - 30 days) stay longer at the trough than those in the later stages, the visiting time at the playing device is increasing with the age of the pigs. This could mean that the pigs are more interested in the playing device the older they get, which is similar to the findings of Stubbe (2000) on the same device.

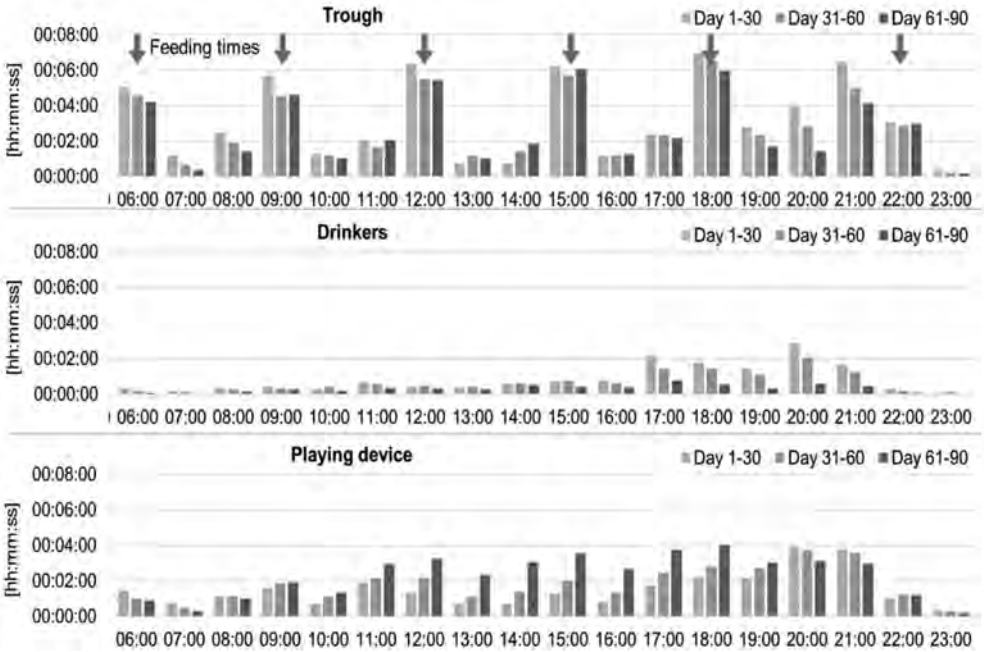

Figure 1. Average visiting time at hotspots during the hours of a day, divided into three fattening stages over all four fattening periods – the arrows indicate the six feeding times throughout the day

A closer look can be made at the individual daily visiting time of each pig which is important because of the high variation as shown earlier. Figure 2 shows the daily duration at the trough of one pig during the fattening period. The visiting time varies between 30 minutes and up to more than 2.5 hours even on 'normal' days. At the end of the fattening period (around fattening day 73), this pig was indicated with a lameness score of two. A few days before that, on fattening day 69, a drop in the visiting time at the trough is visible in the data. For most of the pigs, the development of the daily visiting time at the trough couldn't indicate a lameness strongly enough, because the visiting times didn't change more on days with lameness detection than on 'normal' days. This could be because feeding plays a fundamental role in the life of a pig and is thus the last activity that a pig would forego.

Unfortunately, the data analysis with the daily visiting time at the playing device shows a similar result. The variety between the days is very high, even on an individual pig level, and because of this it is difficult to nearly impossible to detect lameness occurrences by regarding changes in the visiting time at the playing device only.

Another concept of analysis was to look for the time a pig visits a hotspot for the first time at one day. This could indicate changes in the well-being of this pig und thus, it can be a possible way to detect health impacts. Figure 3 shows the time of one pig's first visit per day at the trough after the first feeding time at 6 am in the morning. This pig is very consistent in its morning feeding time, which is almost every day at around 6 am and is not delayed by more than 3 h. At the end of the fattening period, this pig was indicated with a severe lameness on the day, but even then, its behaviour didn't change. Other pigs show a high variation regarding this criterion, making it difficult to detect alterations in the behaviour on days with health issues like lameness.

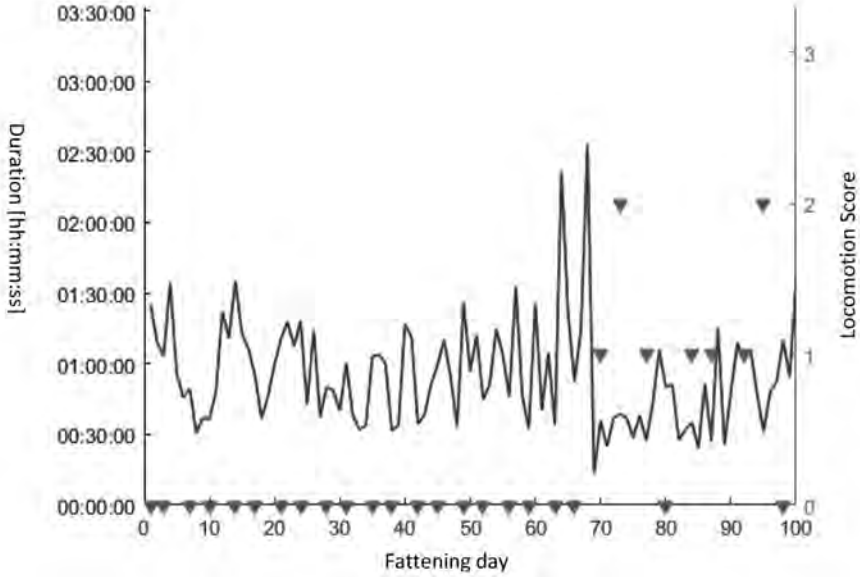

Figure 2. Daily visiting time at the trough of pig 149 (x-axis shows the fattening day, left y-axis the duration time and right y-axis the locomotion score on health observation days, displayed by triangles)

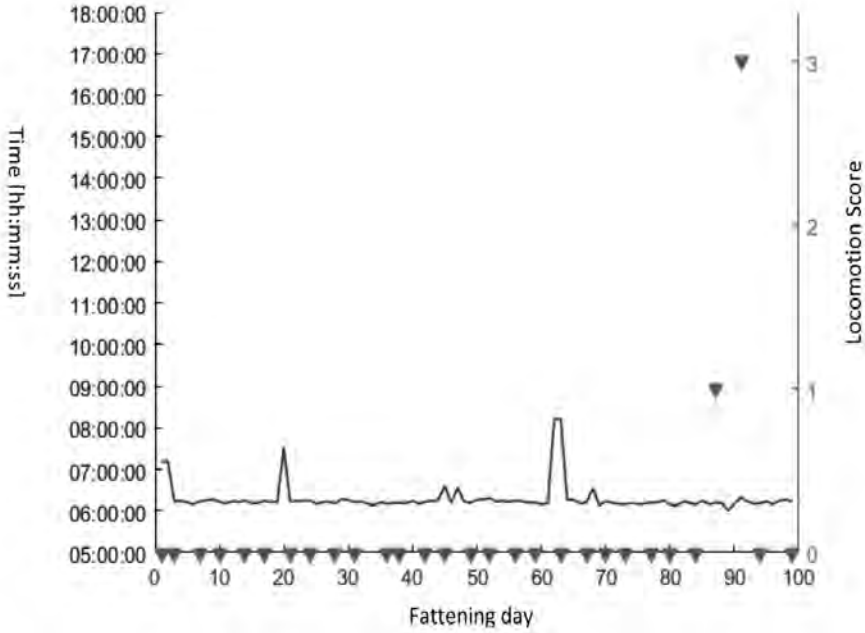

Figure 3. First visit at the trough per day of pig 79 after 6 am during the fattening period (x-axis shows the fattening day, left y-axis the time of day and right y-axis the locomotion score on health observation days, displayed by triangles)

Conclusions

With a UHF-RFID system observing different hotspots in a pen, certain parts of the behaviour of pigs can be monitored continuously. The results of this study show that the analysis of the pigs' behaviour has a promising potential for monitoring of the health status or automatic detection of possible health issues. However, because of the high intra- and inter-animal variability of the behaviour this remains a difficult task, especially regarding changings of behaviour that occur for reasons of health issues. The approaches shown in this article are one-dimensional and insufficient to detect health issues. For detection of health issues, a method that combines different approaches should be pursued. With the UHF-RFID system presented, it is possible to outline the daily events, rhythms and dynamics in the behaviour of pigs within the day continuously.

References

Adrion, F. (2018). Adaption and assessment of a UHF-RFID system for livestock management. Stuttgart, Germany.

Adrion, F., Hammer, N., Eckert, F., Götz, S., and Gallmann, E. (2015). Adjustment of a UHF-RFID system for hotspot monitoring of fattening pigs. In: *Precision Livestock Farming '15. Papers presented at the 7th European Conference on Precision Livestock Farming.* Guarino, M., and Berckmans, D., Milan, Italy, 573–582.

Adrion, F., Kapun, A., Eckert, F., Holland, E.-M., Staiger, M., Götz, S., & Gallmann, E. (2018). Monitoring trough visits of growing-finishing pigs with UHF-RFID. *Computers and Electronics in Agriculture,* 144: 144–153.

Barge, P., Gay, P., Merlino, V., and Tortia, C. (2013). Radio frequency identification technologies for livestock management and meat supply chain traceability. *Canadian Journal of Animal Science,* 93(1): 23–33.

Brown-Brandl, T.M., Rohrer, G.A., and Eigenberg, R.A. (2013). Analysis of feeding behavior of group housed growing-finishing pigs. *Computers and Electronics in Agriculture,* 96: 246–252.

Hammer, N. (2017). *Evaluation of a UHF RFID system for livestock*. Stuttgart, Germany.

Maselyne, J., Adriaens, I., Huybrechts, T., De Ketelaere, B., Millet, S., Vangeyte, J., Van Nuffel, A., and Saeys, W. (2016a). Measuring the drinking behaviour of individual pigs housed in group using radio frequency identification (RFID). *Animal*, 10(9): 1557–1566.

Maselyne, J., Saeys, W., Briene, P., Mertens, K., Vangeyte, J., De Ketelaere, B., Hessel, E.F., Sonck, B., van Nuffel, A. (2016b). Methods to construct feeding visits from RFID registrations of growing-finishing pigs at the feed trough. *Computers and Electronics in Agriculture,* 128: 9–19.

Maselyne, J., Saeys, W., De Ketelaere, B., Mertens, K., Vangeyte, J., Hessel, E.F., Millet, S., and Van Nuffel, A. (2014). Validation of a High Frequency Radio Frequency Identification (HF RFID) system for registering feeding patterns of growing-finishing pigs. *Computers and Electronics in Agriculture,* 102: 10–18.

Matthews, S.G., Miller, A.L., Clapp, J., Plötz, T., and Kyriazakis, I. (2016). Early detection of health and welfare compromises through automated detection of behavioural changes in pigs. *The Veterinary Journal,* 217: 43–51.

Stubbe, A. (2000). *Entwicklung und Beurteilung einer Beschäftigungstechnik für Mastschweine in intensiven Haltungssystemen*. Stuttgart, Germany.

Weary, D.M., Huzzey, J.M., and von Keyserlingk, M.A.G. (2009). Board-invited review: Using behaviour to predict and identify ill health in animals. *Journal of Animal Science,* 87(2): 770–777.

Early disease detection for weaned piglet based on live weight, feeding and drinking behaviour

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Abstract

The aim of this paper is to introduce the results of a first approach for early disease detection at individual level for weaned piglets. The model built is based upon two batches of 102 piglets within the IFIP's experimental pig barn. For each animal we have recorded the individual health status by visual observation three times per week. In the meantime a connected drinker, two connected feeders and a weighing scale recorded individual feeding and drinking behaviour. The dataset has been used to find an algorithm based upon classification able to early detect locomotor, respiratory or digestive disorders with a global accuracy of 88%.

Keywords: early disease detection, real-time analysis, drinking behaviour, feeding behaviour

Introduction

Reduced antibiotic use is one of the main concerns of meat consumers (Grunert *et al.*, 2018), but also one of the recommendations of World Health Organisation for public health (World Health Organisation, 2017). One way to reduce the needs for medication is early disease detection at individual level (Matthews *et al.*, 2016) making the farmer/breeder able to isolate or treat only the sick animal and thus, decrease the risks of disease spreading within the whole room. Subclinical symptoms such as changes in animal behaviour can have a diagnostic value (Andersen *et al.*, 2014; Marcon *et* Rousselière, 2017; Marcon *et al.*, 2018) and even before showing clinical symptoms the water consumption at pen level is decreasing. Modification in feeding and drinking behaviour or in activity can be seen as signs of subclinical disease symptom.

Today, technology offers the possibility of automatic monitoring. It has been shown that pathologic cough can automatically be detected at group level through real-time sounds recording and analysing (Hemeryck *et al.*, 2015). Radio Frequency Identification (RFID) enables the recording of behavioural data at individual level. When it comes to changing the scale of the analysis, from group to individual level, the existing knowledge about changes in behaviour to early detect health disorders has to be rethought. Previous work teaches us that the variability of individual water consumption with healthy piglets (Rousselière *et al.,* 2016) is close to 35% which is very often higher than the changes observed as a subclinical symptom when an animal gets sick. Therefore, the idea of setting a threshold on water consumption is not enough to perform early disease detection. The use of machine learning can be a good way to build a model capable of automatic detection of sub changes in animal behaviour before observing diarrhoea or lameness issues.

The aims of this paper are (i) to present how the early disease detection model has been developed, (ii) the results and (iii) the further developments needed to make the model more specific and accurate.

Material and methods

Housing conditions and animals

The data collection was made at the IFIP experimental farm in Romillé (Brittany, France). After weaning, two batches of 102 piglets from 28–63 days old were allocated in six pens

of 17 animals each. For each batch, piglets were manually weighted, then sorted into three groups of weight (heavy: A & A', medium: B & B' and light: C & C') and finally the RFID ear tag was applied. As shown in Figure1, we used two pens per group.

Figure 1. Housing conditions of piglets sorted by weight

Each pen was equipped with two automatic feeders, one connected to bowl drinkers and one connected to a scale. Within each pen there were eight female and seven castrated male pigs coming from a maximum of four different sows.

The first batch started in November 2017, and the second batch began in March 2018. The piglets were raised up to five weeks. For both trials, the room temperature was maintained, with six infer-red heaters, from 28°C to 24°C with a daily drop in the temperature set point. This temperature set point is similar to what is usually done in French commercial pig barns.

The average weight for both trials were group AA': 9.80 kg ± 0.40, group BB' 8.80 kg ± 0.36 and group CC' 7.69 kg ± 0.36 (Table 1 and 2). During the first batch piglets were, on average, lighter than the second one.

During the first 14 days, the animals received a starter feed. From the 15th day, piglets were fed with a second feed until the end of the test. There was no food transition. The food dispensed to each pen was manually weighed every day. As well as the food consumption, the individual weight of the piglets was manually recorded each week without a fasting period. To check the accuracy of the feed distribution, five doses of food were weighed weekly. However, validation of automata is not part of the scope of this study.

Before the start of the test, the six drinkers are set to obtain a water flow of one litre per minute and all the water pipes are purged. Throughout the test, all the water meters above the drinkers are read once a day.

Table 1. Average weight of the first batch in kilograms of the 17 piglets for each pen and the standard deviation

Pen	Average body weight 28 days old (kg)	Standard deviation
A	9.52	0.37
A'	9.53	0.41
B	8.37	0.48
B'	8.34	0.40
C	6.94	0.60
C'	6.95	0.44

Table 2. Average weight of the second batch in kilograms of the 17 piglets for each pen and the standard deviation

Group	Average body weight 28 days old (kg)	Standard deviation
A	10.10	0.40
A'	10.05	0.45
B	9.22	0.34
B'	8.34	0.40
C	8.43	0.25
C'	8.43	0.17

Animal's health status

For both batches, animals were observed by the station's staff to assess their health status. A specific focus was made on the most frequently observed diseases in pig barns: digestive, locomotor and respiratory disorders. In addition, individual observations on the general health status of piglets were undertaken by a skilled operator every day (five days per week) during the five weeks of trials one and two. The operator observed, over a 20 minute period, each pen and forced all the piglets to defecate three times per week, Monday, Wednesday and Friday. For each of the three main disorders, a score was given related to the severity: 0 is linked to a healthy piglet, 1 the animal begins to show symptom and 2 the symptom is clearly identified. This evaluation was based on a rating grid inspired by the Welfare Quality approach. In addition, all remarks relating to veterinary interventions were recorded as well as all the treatments given to the piglets.

Data and modelling

All the data generated automatically were daily stored within an Acess® database. The sanitary observations were integrated into this database at the end of each batch. The first batch generated 262,137 events with 54 data per event and from the second one 333,792 events were stored. When a piglet was detected in a feeder or a connected drinker it generated an event. Among the 595,965 events, 11% were related to a positive health notation.

All the data were processed with R version 3.3.1 in order to find the best model able to perform early disease detection. Four steps were used: (i) data preparation, (iii) data featuring, (iii) model building and (iv) model testing.

Data preparing: The first step was to prepare the raw database. With 54 variables per event we needed to select which variables were the most important in order to perform early disease detection: we kept 18 of them. Table 3 presents the remaining variables used to perform the next step. The selection was mainly based on zootechnical expertise and depending on which variables were delivered by the automated monitoring to make the early disease detection tools working for commercial farms. For example, we decided not to use the batch ID and the operator ID, which are data dependent on our experimental plan. We kept all the data related to feeding behaviour, such as the time spent in the feeder, the amount of feed consumed per passage, the pig eating time. We did the same with the drinking behaviour and weight.

Table 3. List of variables used to perform machine learning

Pen ID	Animal ID	Sex	Date	Feed consumption	Nb of extra feed doses	Nb of missed feed doses
Time in feeder	Water consumption	Time in drinker	Hour of event	Weight	Fan rate	Room T°
Faecal score	Lameness score	Cough score	Total score			

Data featuring: Before trying to use machine learning, after having selected the variables, some data processing was done. All the data were aggregated per six hours for each day. At this step, there were 14,280 rows of 20 variables per batch (35 days × 102 pigs × 4 hour intervals per day).

In order to smooth the variability in feed and water consumption data and the time spent eating and drinking we added the cumulative value as a new variable and the 12 (4 periods × 6 hour × 3 days) last periods of six hours moving average for each of those four variables.

The way machine learning processing works is that the data are classified row by row without taking into account historical data which can be useful to detect a change in a pattern. As a solution a "lag" function in R was used to add the four last periods of water and feed consumption. On each row of the database we finally have the water and feed consumption of the period p, p-1, p-2, p-3 and p-4.

Because machine learning considers each variable as an independent one, we created new variables by dividing some existing ones by the daily weight of the pig. In fact, the literature shows that water and feed consumption are dependent on the weight of the animal. Therefore, we expressed feed and water consumption per kg live weight. At the end of the data featuring step the remaining data base contained 28,560 rows of 31 variables.

Model building: To select the best machine learning model to detect diseases early, we tested nine different methods: Gradient boosting, Bagging CART, CART, Naïve Bayes, k-nearest neighbour (knn) with k equal to three, five and eight, logistic regression and random forest. For the prediction, the gold standard used was the symptom scoring by operators and we based the learning process to detect the total score. The total score was defined as the sum of faecal, cough and lameness score. For each of these there were three levels: zero – no symptoms observed, one - the animal presents a slight disturbance and two – the animal presents a confirmed disturbance. We reduced the total score as a factor equal to 0 if the sum of faecal, cough and lameness score was lower or equal to two or one if the sum was equal or higher than three. The way the tipping point has been chosen was to ensure at least 5% of the data set will have a health score equal to 1. 7% of the final data base was linked to a positive total health score (THS).

Model testing: for each of the nine machine learning methods used to perform early disease detection, we did 10 iterations. In other words, 10 models by machine learning method were made. The number of iterations was chosen, first, in relation to the computing time needed to run the R script. Then, the very low variation observed for each iteration per method brought us to conclude that 10 iterations were sufficient. The models were built each time on a different sample of data from the featured database. Because there was only 7% of THS, the random dataset has been adjusted to have a proportion of at least

30% of THS. Within each iteration, we randomly select 24% of the data among the 93% of the dataset with a THS equal to 0. Without this sub sampling, machine learning methods would no longer apply.

70% of each dataset was used to train the model and 30% was kept to validate the model. The nine models have been evaluated by analysing the predicted state and the observed one. We used the binary classification test with sensitivity and specificity calculation

Table 4. Confusion matrix

	True condition (given by human observation)	
Predicted	Sick	Healthy
Sick	True positive = TP	False positive = FP
Healthy	False negative = FN	True negative = TN

Sensitivity is the true positive rate which measures the proportion of positives correctly identified (Table 4). The specificity, or true negative rate, measures the proportion of negatives that are correctly identified.

$$Sensitivity = \frac{TP}{(TP + FN)} \qquad Specificity = \frac{TN}{(TN + FP)}$$

Finally, the accuracy measures the global exactitude, the sum of the true positive and the true negative prediction divided by the total number of predictions made.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

Results

The mean sensitivity and specificity obtained for all the models tested were 59% and 85%. This implies that the early disease detection system is working well to predict when a piglet is not sick. In our case, we are looking for a very high sensitivity without decreasing too much the specificity level. Depending on the method used, we removed CART, Gradient boosted, Logistic regression, Naïve Bayes and Random forest with respectively 19%, 14%, 29%, 61% and 69% of sensitivity (Table 5).

The two methods left are knn and Bagging. The knn is a method of classification to estimate the output associated with a new input by taking into account the k training samples whose input is closest to the new input, according to a defined distance. The bagging method is well adapted to small dataset. Bagging perform several iterative sub samples with replacement. For each sub sample a decision tree is built and all the trees are combined to a single model through vote. We can see that for knn, sensitivity and specificity decrease with an increased number of parameters. The best sensitivity results are obtained with knn_3 (88%), but the specificity is lower than the bagging with 81% and 92%, respectively. Thus, the Bagging method seems to be a good compromise with a sensitivity of 83% and a really good specificity. With Bagging, the global accuracy reaches an average of 89%. As shown on Figure 2, the maximum accuracy was 90% in the third iteration and the best sensitivity (85%) during the fifth iteration. The minimum value of accuracy, sensibility and specificity are 88%, 82% and 91%.

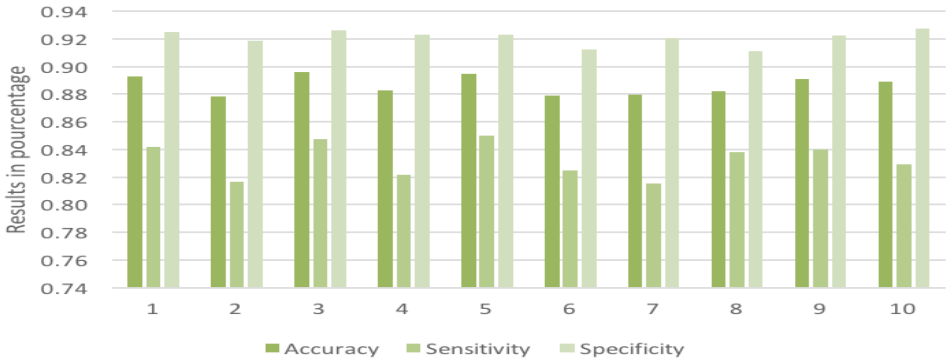

Figure 2. Accuracy, sensitivity and specificity of the bagging methods after ten iterations

Table 5. Average sensitivity and specificity and their standard deviation for the nine tested methods with ten sampling for each

Method used	Sensitivity	SD	Specificity	SD
Bagging	0.83	0.01	0.92	0.01
Classification and regression trees (CART)	0.19	0.06	0.97	0.03
Gradient boosted machine	0.14	0.02	0.99	0.01
k-Nearest neighbours 3	0.88	0.01	0.81	0.00
k-Nearest neighbours 5	0.86	0.01	0.80	0.01
k-Nearest neighbours 8	0.83	0.01	0.78	0.01
Logistic regression	0.29	0.01	0.85	0.01
Naive bayes	0.61	0.04	0.56	0.03
Random forest	0.69	0.01	0.93	0.01

Discussion

The good results obtained with the Bagging method are only the first step to reach a decision support tool for commercial farms. Indeed, with a specificity of 83% the algorithm still emits too many false alarms, which is a risk for breeders to be deterred from using the decision support tool (Berckmans 2014, Hogeveen 2010). As the construction of the model is being based on animals raised under the same conditions, set temperature, genetics, same room, etc., it may not be very robust for different conditions, i.e. it might be context specific. Moreover, data are the information flow that allow Machine Learning to understand and learn. The more data a Machine Learning system receives, the more it learns and the more accurate the results could be. Even when two batches of 102 piglets with daily health status scoring seems to be a big data set for zootechnicians, it is too small a dataset for Machine Learning. That is why we had to correct the database by taking a guided sampling in order to build the algorithm. The main risk is to have an overfitting of the dataset (Dominiak, 2017).

A good way to reduce overfitting risks and to improve machine learning model results could be to have more datasets from different situations. An early disease detection model could also include other traits. Recently Matthews (2016) presented a list of different behavioural categories related to clinical symptoms, such as posture and locomotion. These kind of data were not part of the dataset used in building the bagging model. As an example, pigs infected by salmonella can be more active than others (Rostagno *et al.*, 2011). With the accelerometer fixed on the pig, it is possible to catch its activity and Ahmed (2016) showed that differences in the accelerograms can be observed between a piglet infected by *Salmonella* enteritidis and a healthy one.

Adding new traits could work, but in order to develop a version that is suitable for on-farm use, the cost of the technology must be considered. To make our model run, individual drinking and feeding behaviour have to be automatically recorded which leads to already too costly automation. Having more and more sensors is maybe not the path we have to follow.

Conclusion

The global accuracy of the Bagging model to perform early disease detection appears to be good enough to build a first decision support tool. The results showed that the sensitivity of the model was higher than 83% and the specificity higher than 92%. However, it is difficult to determine whether the model would be robust in another context, with another breed of piglets or within another farm. Further validation of the model is ongoing. New trials with new batches of piglets are being undertaken to see the accuracy of the decision support tool with new piglets (different from the one used to build the model). Further investigations are planned within the Healthy-Livestock project, such as trying to add new traits to find the best predictor of disease or trying to make the model able to determine which kind of disorder the piglets are suffering from.

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References

Ahmed, S.T., Mun, H.S., Islam, M. M, Yoe, H., Yang, C.J. (2016). Monitoring Activity for Recognition of Illness in Experimentally Infected Weaned Piglets Using Received Signal Strength Indication ZigBee-based Wireless Acceleration Sensor. *Anim Sci.,* 149–56.

Andersen, H.M.-L., Dybkjær, L., et Herskin, M.S. (2014). Growing pigs' drinking behaviour: number of visits, duration, water intake and diurnal variation. *Animal,* 8(11): 1881–1888.

Berckmans,. D. (2014). Precision livestock farming technologies for welfare management in intensive livestock systems. (special issue: Animal welfare: focusing on the future.). Revue Scientifique et Technique - Office International des Epizooties, 33: 189–196.

Dominiak, K.N., Spatial Modeling of Drinking Patterns as a Tool for Reducing Alarms in Pig Production (2017 Ph.D. Thesis). The Graduate School of Health and Medical Sciences, University of Copenhagen.

Grunert, K.G., Sonntag, W.I., Glanz-Chanos, V., et Forum, S. (2018). Consumer interest in environmental impact, safety, health and animal welfare aspects of modern pig production: Results of a cross-national choice experiment. *Meat Science*, 137: 123–129.

Hemeryck, M., Berckmans, D., Vranken, E., Tullo, E., Fontana, I., Guarino, M., et van Waterschoot, T. (2015). The Pig Cough Monitor in the EU-PLF project: results and multimodal data analysis in two case studies. *In* Precision Livestock Farming '15. 15 Septembre 2015, Milan, Italie. p. 147–155.

Hogeveen, H.; Kamphuis, C.; Steeneveld, W.; Mollenhorst, H. (2010). Sensors and Clinical Mastitis—The Quest for the Perfect Alert. *Sensors, 10*: 7991–8009.

Marcon, M., et Rousselière, Y. (2017). Post-sevrage, utilité d'un nourrisseur connecté. Tech Porc, n° 35. p. 34–35.

Marcon, M., Rousselière, Y., et Hémonic, A. (2018). Développement d'un dispositif de pesée individuelle et automatisée des porcelets en post-sevrage. *In* 50èmes Journées de la Recherche Porcine - 2018. 6 Février 2018, Paris, France. p. 243–244.

Matthews, S.G., Miller, A.L., Clapp, J., Plötz, T., et Kyriazakis, I. (2016). Early detection of health and welfare compromises through automated detection of behavioural changes in pigs. The Veterinary Journal, 217: 43–51.

Rostagno, M.H., Eicher, S.D., Lay, D.C. (2011).Immunological, physiological, and behavioral effects of *Salmonella* enterica carriage and shedding in experimentally infected finishing pigs. *Foodborne Pathogens and Disease*, 8: 623–630.

Rousselière, Y., Hémonic, A., et Marcon, M. (2016). Suivi individuel du comportement d'abreuvement du porcelet sevré. *In* 48èmes Journées de la Recherche Porcine - 2016. 2 Février 2016, Paris, France. p. 355–356.

World Health Organization. (2017). WHO guidelines on use of medically important antimicrobials in food-producing animals. ISBN 978-92-4-155013–0.

Precision Livestock Farming as a mitigation strategy for livestock farming environmental impact: a review

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Abstract

The primary goal of Precision Livestock Farming (PLF) is to make intensive livestock farming more economically, socially and environmentally sustainable and this can be obtained through the observation, interpretation of behaviours and, if possible, individual management of animals. Furthermore, adopting PLF to support management strategies may lead to the reduction of the environmental impact of farms. To date, the environmental impact of livestock farming can be mitigated by the adoption of several practices, such as technical improvements (manure treatments, intensification, management strategies) and/or dietary changes. Although PLF is not yet designed to directly reduce the environmental impact of livestock farming, several authors claim that it is possible. The great potential of PLF relies on early warnings, that give the farmer the possibility to take action as soon as the first signals of impaired welfare or health appear. As an example, the use of real time technology (sensors, microphone and preventive diagnostic tools) has the potential to improve animal welfare, increase the performance, and minimise the environmental footprint. Indeed, improving animal health and reducing animal morbidity and mortality have the potential to increase the saleable output, and dilute non-CO_2 emissions per unit product, and could represent an effective strategy to limit the use of antibiotics. Good productive performance that relies on animal health and welfare achieved through PLF can mitigate the environmental impact of livestock. More studies are necessary to extend the actual potential of PLF as a mitigation strategy. Undeniably, if this potential is confirmed, PLF could enter among the BATs.

Keywords: Precision livestock farming, environmental impact, mitigation strategy, livestock farming

Introduction

Industrial-scale livestock production is the most common and widespread means of livestock production and occurs within facilities known as concentrated, or confined, animal feeding operations (CAFOs) (Mallin *et al.*, 2015) that can generate large quantities of manure (Ebner, 2017) far from areas of intensive crop farming where the excreta could be used as fertiliser (Li *et al.*, 2016). The livestock sector is an important user of natural resources and has significant influence on air quality, global climate, soil quality, biodiversity and water quality, by altering the biogeochemical cycles of nitrogen, phosphorus and carbon, giving rise to environmental concerns (Leip *et al.*, 2015). Therefore, livestock farming should be oriented towards more sustainable systems, applying management strategies and technologies to reach this goal. According to Berckmans (2014), the application of Precision Livestock Farming (PLF) could be a good approach to reach the environmental sustainability of livestock farming, since it allows control of animal health and welfare and the microclimate of the barn. PLF is defined as: "the application of process engineering principles and techniques to livestock farming to automatically monitor, model and manage animal production" and converting bio response into relevant information that can easily be applied to different management aspects focusing on the animal and on the

environment (Emanuela Tullo *et al.*, 2017). The primary goal of PLF is to make livestock farming more economically, socially and environmentally sustainable (Vranken & Berckmans, 2017). PLF can be applied to monitor animal growth and behaviour, product yield, endemic disease and the physical environment of livestock buildings including the microenvironment and the emission of gaseous pollutants (Fournel *et al.*, 2017).

To-date, PLF technologies have been developed and applied to improve health and consequently the welfare of animals (Neethirajan *et al.*, 2017) to improve traceability (Lima *et al.*, 2018; Monteiro *et al.*, 2017; Vranken & Berckmans, 2017), and to create added value to the farmer (Halachmi *et al.*, 2015; Kamphuis *et al.*, 2015; Lopes *et al.*, 2016). With PLF, farmers can ensure good health and welfare of his animals, reaching good productive and reproductive performance, and lower the environmental impact per unit of animal product. Ensuring animal health and welfare is necessary to obtain good productive and reproductive performance, lowering the environmental impact per unit of animal product.

PLF as a mitigation strategy

To-date, the environmental impact of livestock farming can be mitigated by the adoption of several practices, such as technical improvements (manure treatments, intensification, management strategies) and/or dietary changes. Although PLF is not designed to directly reduce the environmental impact of livestock farming, several authors claim that it is possible (Berckmans, 2017; Llonch *et al.*, 2017). Indeed, adopting PLF to support management strategies can lead to the reduction of a farms environmental impact. According to Zhang *et al.* (2013) emissions of NH_3 can be reduced by 60-65% through the application of a PLF system for the management of the ventilation.

Figure 1. Summary of the potential mitigation effects derived from the application of PLF technologies

Animal welfare

The great potential of PLF relies on early warnings, that give the farmer the possibility of taking action as soon as first signals of impaired welfare or health appear (Dominiak & Kristensen, 2017). As an example, the use of real time technology (sensors, microphone and preventive diagnostic tools) has the potential to improve animal welfare, increase the technical results, and minimise the environmental footprint (Van Hertem *et al.*, 2017). This potential was validated by several authors with a Life Cycle Assessment approach (Chen *et al.*, 2016; Todde *et al.*, 2017). Behind PLF is an accurate development of prediction models, that are able to send alert messages to farmers based on animal and environmental input information (health, welfare, behaviour, micro-climate), and may help in identifying any deviation from the normal pattern.

To this purpose, several PLF devices have been demonstrated to be effective in the control of dairy cows feeding behaviour and rumination in intensive and extensive conditions (Pereira *et al.*, 2018; Reiter *et al.*, 2018; Werner *et al.*, 2018). Rumination and feeding behaviour depend on the quality of forage and on the level of feed intake and are related to the emission of methane, depending on the quality of the silage, and it is possible to obtain a reduction of CH_4 emission of up to 11% (Blaise *et al.*, 2017; Warner *et al.*, 2017). Therefore, managing and continuously controlling these parameters can be the correct strategy to reduce environmental impact.

Animal health

As stated by Llonch *et al.* (2017) environmental impact can be reduced by limiting unwanted emissions that can occur when animals face health and stress problems, so, numerous PLF tools have been applied to dairy cattle to detect lameness, subacute rumen acidosis and impaired rumen functionality and mastitis.

Regarding lameness, depending on the severity of the pathology, it may cause environmental impact increases of more than 7–9% for global warming, acidification, eutrophication and fossil fuel depletion (Chen *et al.*, 2016). According to their results, it is clear that the implementation of real time management systems has the potential to make a positive meaningful contribution on the environmental impact and economic aspect of dairy farming. Considering mastitis, Hospido & Sonesson (2005) predicted a reduction of 2.5% (GWP) to 5.8% (depletion of abiotic resources) as a consequence of the decrease in clinical (from 25–18%) and sub-clinical mastitis rates (from 33–15%), making important and relevant the prevention of this pathology.

Among indirect mitigation strategies aiming to reduce the environmental impact of livestock farming there is also the correct management of fertility. It has been estimated that if fertility is maintained at the maximum rates, it is possible to reduce GHG emissions by more than 20% per herd (Wilkinson & Garnsworthy, 2017). Bell *et al.* (2014) showed that improved efficiencies of production associated with health and fertility, as well as feed efficiency in dairy farms, could reduce GHG emissions by 0.9% per unit of product. According to several studies, PLF tools can be useful in herd fertility management because the correct moment for insemination in cows and sheep can be detected through devices, algorithms, and sensors, increasing conception rates and therefore the success of mitigation strategies. According to Gerber *et al.* (2013), improving animal health and reducing animal morbidity and mortality has the potential to reduce both CH_4 and N_2O from enteric fermentation and animal manure, providing benefits to the livestock producer. Undeniably, reduced mortality and morbidity lead to greater saleable output, diluting non-CO_2 emissions per unit product. Preserving animal health has another environmental benefit; reducing antibiotic use is an effective strategy to limit the antibiotic resistance phenomena (Thanner *et al.*, 2016).

Diagnostic tools based on PLF principles (autonomous, continuous, real-time monitoring and control of all aspects of livestock management) can provide a valuable support to accurately manage and monitor animal health (Neethirajan *et al.*, 2017). Behavioural changes that precede or accompany subclinical and clinical diseases may have diagnostic value (Matthews *et al.*, 2016). Technological advances and validation of ideas and prototypes lead to the development of PLF diagnostic tools able to identify problems in the farm without handling or stressing animals and give the possibility to recognize a disease outbreak days before the farmer (King, 2017). Several PLF diagnostic tools have been developed so far, to identify respiratory diseases in pigs and calves through sound analysis, to control helminth infection of ruminants with image analysis and to detect

coccidiosis in poultry farms through the analysis of volatile organic compounds emitted by infected birds (Carpentier *et al.*, 2018; Grilli *et al.*, 2018; Tullo *et al.*, 2017; Vandermeulen *et al.*, 2016; Vercruysse *et al.*, 2018).

All the above-mentioned systems allow the early detection of pathologies as soon as the first symptoms appear; in this way it is possible to treat a restricted number of animals (no mass treatment) or to use principles other than antimicrobials (Grilli *et al.*, 2018). This could be a real, environmental friendly, and effective solution to try to solve the problem of antibiotic pollution, that, at the moment, represents a serious problem for human and animal health (Laxminarayan *et al.*, 2016).

Housing

Regarding housing management, only few studies focused on the relationship between PLF and environmental impact. The more relevant papers focused on ventilation to improve indoor air quality in pig houses (Zhang *et al.*, 2013), measuring procedures for ammonia emission (Vranken *et al.*, 2013), monitoring dust in poultry houses (Demmers *et al.*, 2015; Peña Fernández *et al.*, 2017) and on the application of PLF to obtain environmentally friendly poultry production (Bartzanas *et al.*, 2015). All these technical solutions appeared to be effective in reducing the environmental impact of pig and poultry farming.

Energy saving

PLF technologies could also be applied to reduce carbon footprint. As reported by Todde *et al.* (2017) a real time milk analysis and separation system could allow a sensible reduction of energetic costs for cheese production. This system allows the re-organisation of milk logistic according to the milks coagulation property, in order to deliver milk with high casein content directly to the cheese factory, saving about 44% of energy and reducing the emissions of CO_2 by 69%.

Economic aspects

Fountas *et al.* (2015) focussed on profitability of the system, since cost for investment often represents the main obstacle to adopt PLF systems (Hartung *et al.*, 2017). They highlighted the benefits for the farmers such as the improved decision making, the attraction of young farmers and the positive influence in resolving the analytical shortcomings of the end user (farmer) by transforming raw data into useful information, through analysis and expert interpretation.

Non-tangible aspects

The EU-PLF project was running PLF technology cases upon the use of cameras, microphones and sensors on broilers, fattening pigs and milking cows on 20 farms in Europe. On each species, 60 production cycles were measured and a lot of information was collected. Regarding the return on investment it is clear the farmer needs to be familiar with the system to use it in his management. The farmers participated in several workshops during the project where the researchers discussed with them the benefits and the good and bad experiences with the PLF technology. It is clear that farmers search for a tangible return on investment, but they also clearly stated that there are important non-tangible advantages such as lifestyle, being able to bring the kids to school or to participate in community events, peace of mind, etc. These non-tangible advantages might become increasingly important to attract young farmers into the sector since we want farmers to be able to live their life like all other professions. Knowing that PLF systems guard their animals day and night might be of high importance.

Conclusions

PLF is designed to monitor continuously and in real time animal health and welfare, while environmental impact and climate change mitigation strategies are, so far, not primary goals. As reported by many authors, livestock environmental impact mitigation can be obtained through enhancing productivity levels, reproduction traits, and maintaining good health. Regarding antibiotic pollution, the overall banning of antibiotic use in livestock farming is impractical but the use can be more efficient. Therefore, there is the necessity to develop and apply methods and technologies to improve the efficacy of treatments and to decrease the incidence of infections by improving the conditions under which animals are raised. PLF constant monitoring allows the farmer to intervene as soon as animals show the first signs of impaired welfare or illness. Rapid intervention, in the case of disease, or modification of the management strategy, in the case of stress, can actually and effectively improve the animal status. Thus, good productive performance that relies on animal health and welfare achieved through PLF can mitigate the environmental impact of livestock, and reduce the emergence and dissemination of resistant bacteria in the environment. Comparing PLF to already verified mitigation strategies appears to be a valid tool to improve animal health and welfare, overall income and the environment. Surely, the introduction of new technologies and management techniques poses several issues related to the ethics of food animal production, human workforce, animal-human relationship, and environmental burden relative to the production and operating PLF device on farms. There is a social consensus that agriculture should not be industrialised, but the introduction of simple technologies such as Bluetooth, GPS or RFID in farms offers the opportunity to modify the duration of work, the content and the nature of the tasks carried out by farmers, their mental workload, and the relationship between farmers and their animals (Wathes *et al.*, 2008). Currently, few studies reported PLF efficacy in the reduction of the environmental impact, and indeed more studies are necessary to extend the actual potential of PLF as a mitigation strategy. Undeniably, if this potential is confirmed, PLF techniques could enter among the BATs, according to BREF prescriptions.

References

Bartzanas, T., Papanastasiou, D.K., Skoufos, I., Tzora, A., Fidaros, D., Baxevanou, C., Panagakis, P., & Kittas, C. (2015). Environmental friendly poultry production using novel precision livestock techniques. In *Precision Livestock Farming 2015 - Papers Presented at the 7th European Conference on Precision Livestock Farming, ECPLF 2015* (pp. 811–819).

Bell, M.J., Garnsworthy, P.C., Stott, A.W., & Pryce, J.E. (2014). Effects of changing cow production and fitness traits on profit and greenhouse gas emissions of UK dairy systems. *The Journal of Agricultural Science*, *153*(01): 138–151. https://doi.org/10.1017/s0021859614000847.

Berckmans, D. (2014). Precision livestock farming technologies for welfare management in intensive livestock systems. *Rev Sci Tech*, *33*(1): 189–196. Retrieved from https://www.ncbi.nlm.nih.gov/pubmed/25000791.

Berckmans, D. (2017). General introduction to precision livestock farming. *Animal Frontiers*, *7*(1): 6–11.

Blaise, Y., Andriamandroso, A., Heinesch, B., Beckers, Y., Castro Muñoz, E., Lebeau, F., & Bindelle, J. (2017). Influences of feeding behaviour and forage quality on diurnal methane emission dynamics of grazing cows. *Precision Livestock Farming '17*, 759–769.

Carpentier, L., Berckmans, D., Youssef, A., Berckmans, D., van Waterschoot, T., Johnston, D., Ferguson, N., Earley, B., Fontana, I., Tullo, E., Guarino, M., Vranken, E., & Norton, T. (2018). Automatic cough detection for bovine respiratory disease in a calf house. *Biosystems Engineering*, *173*. https://doi.org/10.1016/j.biosystemseng.2018.06.018.

Chen, W., White, E., & Holden, N.M. (2016). The effect of lameness on the environmental performance of milk production by rotational grazing. *Journal of Environmental Management*, 172: 143–150.

Demmers, T.G.M., Tong, Q., Rooijakkers, L., & Koenders, E. (2015). Monitoring dust concentration in broiler houses. In *Precision Livestock Farming 2015 - Papers Presented at the 7th European Conference on Precision Livestock Farming, ECPLF 2015* (pp. 525–530).

Dominiak, K.N., & Kristensen, A.R. (2017). Prioritizing alarms from sensor-based detection models in livestock production - A review on model performance and alarm reducing methods. *Computers and Electronics in Agriculture*, *133*, 46–67. https://doi.org/10.1016/j.compag.2016.12.008.

Ebner, P. (2017). CAFOs and Public Health: Pathogens and Manure. *PUBLIC HEALTH*, *501*, 356.

Fountas, S., Carli, G., Sørensen, C.G., Tsiropoulos, Z., Cavalaris, C., Vatsanidou, A., Liakos, B., Canavari, M., Wiebensohn, J., & Tisserye, B. (2015). Farm management information systems: Current situation and future perspectives. *Computers and Electronics in Agriculture*, 115: 40–50.

Fournel, S., Rousseau, A.N., & Laberge, B. (2017). Rethinking environment control strategy of confined animal housing systems through precision livestock farming. *Biosystems Engineering*, 155: 96–123.

Gerber, P.J., Henderson, B., & Makkar, H.P.S. (2013). *Mitigation of greenhouse gas emissions in livestock production. A review of technical options for non-CO_2 emissions*. FAO.

Grilli, G., Borgonovo, F., Tullo, E., Fontana, I., Guarino, M., & Ferrante, V. (2018). A pilot study to detect coccidiosis in poultry farms at early stage from air analysis. *Biosystems Engineering*.

Halachmi, I., Tello, A.S., Fernández, A.P., van Hertem, T., Sibony, V., Weyl-Feinstein, S., Verbrugge, A., Bonneau, M., & Neilson, R. (2015). 5. Discussion: how PLF delivers added value to farmers. In *Precision livestock farming applications: Making sense of sensors to support farm management* (pp. 113–118). Wageningen Academic Publishers.

Hartung, J., Banhazi, T., Vranken, E., & Guarino, M. (2017). European farmers' experiences with precision livestock farming systems. *Animal Frontiers*, *7*(1): 38–44.

Hospido, A., & Sonesson, U. (2005). The environmental impact of mastitis: a case study of dairy herds. *Science of the Total Environment*, *343*(1–3): 71–82.

Kamphuis, C., Steeneveld, W., & Hogeveen, H. (2015). 2. Economic modelling to evaluate the benefits of precision livestock farming technologies. In *Precision livestock farming applications: Making sense of sensors to support farm management* (pp. 163–171). Wageningen Academic Publishers.

King, A. (2017). Technology: The Future of Agriculture. *Nature*, *544*(7651), S21–S23. https://doi.org/10.1038/544S21a.

Laxminarayan, R., Sridhar, D., Blaser, M., Wang, M., & Woolhouse, M. (2016). Achieving global targets for antimicrobial resistance. *Science*, *353*(6302): 874–875. https://doi.org/10.1126/science.aaf9286.

Leip, A., Billen, G., Garnier, J., Grizzetti, B., Lassaletta, L., Reis, S., Simpson, D., Sutton, M.A., De Vries, W., & Weiss, F. (2015). Impacts of European livestock production: nitrogen, sulphur, phosphorus and greenhouse gas emissions, land-use, water eutrophication and biodiversity. *Environmental Research Letters*, *10*(11), 115004.

Li, F., Cheng, S., Yu, H., & Yang, D. (2016). Waste from livestock and poultry breeding and its potential assessment of biogas energy in rural China. *Journal of Cleaner Production*, *126*: 451–460.

Lima, E., Hopkins, T., Gurney, E., Shortall, O., Lovatt, F., Davies, P., Williamson, G., & Kaler, J. (2018). Drivers for precision livestock technology adoption: A study of factors associated with adoption of electronic identification technology by commercial sheep farmers in England and Wales. *PLoS One*, *13*(1), e0190489. https://doi.org/10.1371/journal.pone.0190489.

Llonch, P., Haskell, M.J., Dewhurst, R.J., & Turner, S.P. (2017). Current available strategies to mitigate greenhouse gas emissions in livestock systems: an animal welfare perspective. *Animal*, *11*(2): 274–284.

Lopes, S.I., Bexiga, R., Araújo, J.P., Cerqueira, J.L., Abreu, C., Paredes, C., & Alonso, J.M. (2016). Precision livestock farming for reproductive performance optimization: a survey. In *Food futures: ethics, science and culture* (pp. 3197–3211). Wageningen Academic Publishers.

Mallin, M.A., McIver, M.R., Robuck, A.R., & Dickens, A.K. (2015). Industrial Swine and Poultry Production Causes Chronic Nutrient and Fecal Microbial Stream Pollution. *Water, Air, & Soil Pollution*, *226*(12), 407. https://doi.org/10.1007/s11270-015-2669-y.

Matthews, S.G., Miller, A.L., Clapp, J., Plotz, T., & Kyriazakis, I. (2016). Early detection of health and welfare compromises through automated detection of behavioural changes in pigs. *Vet Journal*, *217*: 43–51. https://doi.org/10.1016/j.tvjl.2016.09.005.

Monteiro, A., Bertol, T.M., De Oliveira, P.A. V, Dourmad, J.-Y., Coldebella, A., & Kessler, A.M. (2017). The impact of feeding growing-finishing pigs with reduced dietary protein levels on performance, carcass traits, meat quality and environmental impacts. *Livestock Science*, *198*: 162–169.

Neethirajan, S., Tuteja, S.K., Huang, S.T., & Kelton, D. (2017). Recent advancement in biosensors technology for animal and livestock health management. *Biosens Bioelectron*, *98*: 398–407. https://doi.org/10.1016/j.bios.2017.07.015.

Peña Fernández, A., Tong, Q., Youssef Ali Amer, A.L.I., Norton, T., Demmers, T., & Berckmans, D. (2017). Monitoring dust concentration in poultry houses using broiler activity and ventilation rate.

Pereira, G.M., Heins, B.J., & Endres, M.I. (2018). Technical note: Validation of an ear-tag accelerometer sensor to determine rumination, eating, and activity behaviors of grazing dairy cattle. *Journal of Dairy Science*, *101*(3): 2492–2495. https://doi.org/10.3168/jds.2016–12534.

Reiter, S., Sattlecker, G., Lidauer, L., Kickinger, F., Öhlschuster, M., Auer, W., Schweinzer, V., Klein-Jöbstl, D., Drillich, M., & Iwersen, M. (2018). Evaluation of an ear-tag-based accelerometer for monitoring rumination in dairy cows. *Journal of Dairy Science*, *101*(4): 3398–3411. https://doi.org/10.3168/jds.2017–12686.

Thanner, S., Drissner, D., & Walsh, F. (2016). Antimicrobial Resistance in Agriculture. *MBio*, *7*(2), e02227–15. https://doi.org/10.1128/mBio.02227–15.

Todde, G., Caria, M., Gambella, F., & Pazzona, A. (2017). Energy and Carbon Impact of Precision Livestock Farming Technologies Implementation in the Milk Chain: From Dairy Farm to Cheese Factory. *Agriculture*, *7*(10). https://doi.org/10.3390/agriculture7100079.

Tullo, E., Borgonovo, F., Fontana, I., Grilli, G., Guarino, M., & Ferrante, V. (2017). Validation of an early warning system for enteric disorders in broiler farming. In *Precision Livestock Farming 2017 - Papers Presented at the 8th European Conference on Precision Livestock Farming, ECPLF 2017*.

Tullo, Emanuela, Fontana, I., Diana, A., Norton, T., Berckmans, D., & Guarino, M. (2017). Application note: Labelling, a methodology to develop reliable algorithm in PLF. *Computers and Electronics in Agriculture*, 142: 424–428.

Van Hertem, T., Rooijakkers, L., Berckmans, D., Peña Fernández, A., Norton, T., Berckmans, D., & Vranken, E. (2017). Appropriate data visualisation is key to Precision Livestock Farming acceptance. *Computers and Electronics in Agriculture*, 138: 1–10. https://doi.org/https://doi.org/10.1016/j.compag.2017.04.003.

Vandermeulen, J., Bahr, C., Johnston, D., Earley, B., Tullo, E., Fontana, I., Guarino, M., Exadaktylos, V., & Berckmans, D. (2016). Early recognition of bovine respiratory disease in calves using automated continuous monitoring of cough sounds. *Computers and Electronics in Agriculture*, *129*: 15–26.

Vercruysse, J., Charlier, J., Van Dijk, J., Morgan, E.R., Geary, T., von Samson-Himmelstjerna, G., & Claerebout, E. (2018). Control of helminth ruminant infections by 2030. *Parasitology*, 1–10. https://doi.org/10.1017/S003118201700227X.

Vranken, E., & Berckmans, D. (2017). Precision livestock farming for pigs. *Animal Frontiers*, *7*(1): 32–37.

Vranken, E., Cabaraux, J.-F., & Berckmans, D. (2013). Development of a simplified measuring procedure for ammonia emission from agricultural constructions. *Precision Livestock Farming '13*, 899.

Warner, D., Bannink, A., Hatew, B., van Laar, H., & Dijkstra, J. (2017). Effects of grass silage quality and level of feed intake on enteric methane production in lactating dairy cows1. *Journal of Animal Science*, *95*(8): 3687–3699. https://doi.org/10.2527/jas.2017.1459.

Wathes, C.M., Kristensen, H.H., Aerts, J.M., & Berckmans, D. (2008). Is precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall? *Computers and Electronics in Agriculture*. https://doi.org/10.1016/j.compag.2008.05.005.

Werner, J., Leso, L., Umstatter, C., Niederhauser, J., Kennedy, E., Geoghegan, A., Shalloo, L., Schick, M., & O'Brien, B. (2018). Evaluation of the RumiWatchSystem for measuring grazing behaviour of cows. *Journal of Neuroscience Methods*, *300*: 138–146. https://doi.org/https://doi.org/10.1016/j.jneumeth.2017.08.022.

Wilkinson, J.M., & Garnsworthy, P.C. (2017). Impact of diet and fertility on greenhouse gas emissions and nitrogen efficiency of milk production. *Livestock*, *22*(3): 140–144.

Zhang, G., Kai, P., & Zong, C. (2013). Precision ventilation to improve indoor air quality and reduce ammonia emission of pig production housing. In *Precision Livestock Farming 2013 - Papers Presented at the 6th European Conference on Precision Livestock Farming, ECPLF 2013* (pp. 883–892).

Effect of automated systems on the working time requirement in dairy farms

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Abstract

Working time is considered to be one of the main resources in agriculture. Data create the basis for strategic planning of work processes and for optimising production. This paper focuses on analysing working time requirement of different work processes to compare conventional feeding systems (CFS) and automatic feeding systems (AFS). Time data for various operations and working equipment were measured using video-based technology and time recording software. The evaluated data set provided the basis for data modelling and integration into a modularly structured calculation system. The modelling was focused on different assumptions regarding working time elements, technical details, feeding strategies and structural parameters. Four herd sizes of 60, 120, 180 and 240 cows were selected. The daily working time requirement was markedly influenced by herd size and feeding system. Feeding 60 cows using a CFS had a working time requirement of 43.6 manpower minutes (MPmin) day^{-1} whereas the AFS accounted for a time requirement of 12.9 MPmin day^{-1}. The daily time needed for feeding enhanced with increasing herd size and decreased using AFS (120 cows: 71.6 MPmin (CFS) versus 16.0 MPmin (AFS), 180 cows: 97.7 MPmin versus 22.3 MPmin, 240 cows: 123.8 MPmin versus 28.5 MPmin).

In conclusion, knowledge of working time requirement provides valuable calculation information and supports decision making at specific stages of the production and work process. Time scarcity can be managed by intelligently applying innovative technology.

Keywords: working time requirement, work analysis, calculation model, automated systems

Introduction

Precison Livestock Farming is defined as the use of automated systems to measure various animal- and production-related indicators (Reith & Hoy, 2018). As working time becomes a criterion of scarcity due to the increase in average herd size; there is also a trend towards the automation of work processes, thus encouraging the adoption of precision systems in dairy farms (Gargiulo *et al.,* 2018). Other aspects influencing the adoption of innovative technologies are cost reduction and facilitating factors (Pierpaoli *et al.,* 2013). Working time data including all relevant elements of the work system can be used for model calculations reflecting the agricultural practice (Gindele, 1972). They are a prerequisite for medium- and long-term planning processes. The decision to implement new systems represents a significant investment for a dairy farmer, who often faces the challenge of choosing a technology that will serve the needs for several years (Boehlje & Schiek, 1998). Additionally, data on working time requirements are indispensable for developing strategies and showing alternative solutions in agriculture (Auernhammer, 1976). Various systems with different degrees of automation are available on the market and are gaining in importance. Growing dairy farms demand a simplification of the labour economy by increasing the efficiency of labour management (and lifestyle). This also applies to questions relating to feeding technologies and strategies (Schingoethe, 2017). The aim is to optimise the work system by analysing systematically and designing the technical, organisational and social conditions of work processes. To fulfil a work task, a working person as the active and most important

element in the work system interacts with other elements. Not only the interrelationships between persons and technology are relevant, but also work organisation. The individuals' work situation and function as a part of the work system form the focus of consideration (Auernhammer, 1976). To find the most efficient use of working time the aim of this paper is to determine the working time requirements of different work processes necessary for feeding cows. The time studies and the following model calculations were designed to analyse and to compare the effects of conventional and automated feeding systems on working time requirement in dairy farms.

Material and methods

Data acquisition

The work process was broken down into easily identifiable and clearly described work elements, the smallest practicable units that can be timed with a stop-watch or a special time recording system (Kanawaty, 1992). Data were obtained at the work element level for the four herd sizes of 60, 120, 180 and 240 cows selected. They were measured by tablet, pocket PC and time recording software (ORTIM-system (dmc-group), MEZA (Drigus)). The software provides the possibility to insert video files and statistical analyses. Further calculations were made using Microsoft Excel 2016. A detailed description of the work system and a precise definition of the start and end time of sections are essential for representative study findings being applicable to different agricultural production systems. Data were integrated into a time database as the basis for the calculation system. The influencing factors were compiled into a list of variables and auxiliary variables and linked to the work elements using mathematical formulae. The working time requirement was modelled and calculated for feeding cows a total mixed ration (TMR) diet (Table 1) by a conventional feeding system (CFS) using a feed mixer wagon and for feeding cows by an automatic feeding system (AFS). Information on automatic feeding techniques is described by Da Borso *et al.* (2017).

Table 1. Composition of the total mixed ration (TMR)

Components	Feed intake, kg FM (cow and day)$^{-1}$	Feed intake, kg DM (cow and day)$^{-1}$	Ration composition, %	Density, Mg (m^3)$^{-1}$
Grass silage	14	5.0	32.6	0.65
Corn silage	20	6.6	46.6	0.70
Hay	2	1.8	4.6	0.01
Rapeseed meal	1	0.9	2.3	0.54
Barley	2	1.8	4.6	0.60
Concentrate	4	3.5	9.3	0.60
Total	43.4	19.6	100	-

Definition of the models

The CFS-model was based on the following assumptions:

- Loading and distribution of the TMR are performed once a day
- Group size: 60 lactating cows
- Volume of the feed mixer wagon: 10 m^3

The assumptions of the AFS-model can be listed as follows:

- The AFS consists of a self-loading device with six feed storage tanks (the silages are temporarily stored in blocks)
- The distribution is automatically performed several times a day
- The feeding technology is controlled twice a day
- Volume of the feed storage tank: 10 m^3
- Volume of the wagon distributing the ration: 3 m^3

For both models, removal and transport of the fodder components are done by a silage cutter (volume: 1.2 m^3) and a tractor shovel (volume: 0.75 m^3). Mechanisation, distances and TMR composition are identical.

Construction of the workflow

Before modelling, the workflow was divided into different sections (Figures 1 and 2). Each phase consists of specific work elements and factors affecting the working time requirement. Depending on the required frequency (e.g. number of components, number of loadings in dependence of the mechanisation, number of lactation groups), individual sub-processes are repeated so that different cycles can be defined; or decisions have to be made. Using the time classification described by Reith *et al.* (2017), the individual work processes can be assigned to the corresponding times.

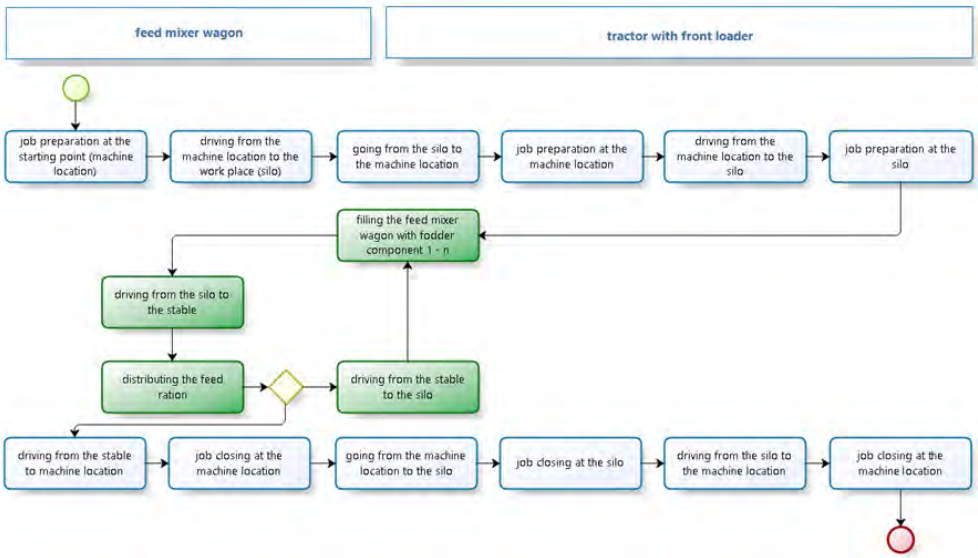

Figure 1. Flowchart for feeding cows by a conventional feeding system (CFS) using a feed mixer wagon

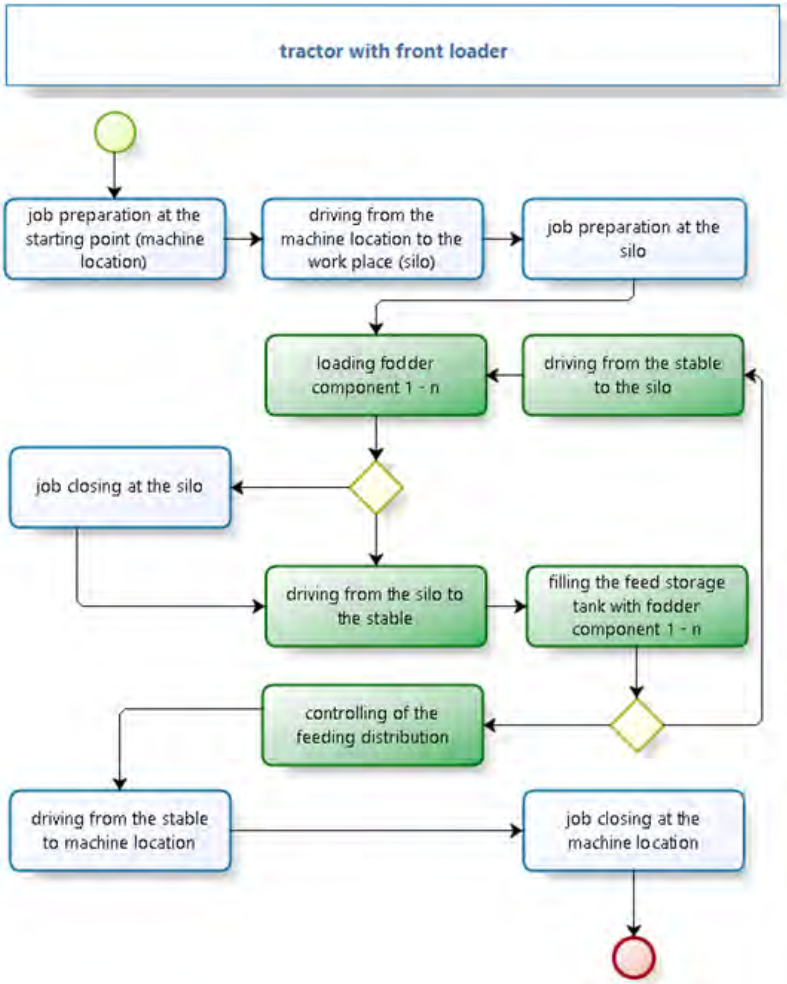

Figure 2. Flowchart for feeding cows by an automatic feeding system (AFS)

Results and discussion

For both models, the working time requirement depending on a wide range of influencing factors was calculated for four variants (60, 120, 180, 240 cows). The modelling showed that daily working time was influenced by size of dairy herds and feeding technology. Šístkova *et al.* (2015) emphasised the importance of the accuracy of dosing the individual components into the ration. When loading, the most relevant factors are the used technique (loaders, hoppers, chopping, devices, silage cutters), physical properties of the individual fodder components (size, shape and density), the loaded weight of components as well as human factors (expertise and responsibility).

The feeding system with a mixer wagon was chosen as CFS-model, because feeding mixed rations has evolved for improved management during the last 50 years. With regard to labour economy, this technology allows the feeding of larger herds faster than feeding components separately (Schingoethe, 2017).

The time required to feed 60 cows by a CFS was 43.6 manpower minutes (MPmin) day^{-1} (Figure 3). The daily feeding working time requirement increased with increasing herd size (120 cows: 71.6 MPmin, 180 cows: 97.7 MPmin, 240 cows: 123.8 MPmin). The calculation included the times for job preparation and job closing at the starting and ending point of the work process (machines set-up time and the corresponding shut-down time), the times for job preparation and job closing at work site (opening and closing the silage protection cover), the loading time and the time for distributing the TMR. After mixing the components, the TMR was characterised by a volume of 8.70 m^3. Thus, a feed mixer wagon with the assumed 10 m^3 mixing volume was sufficient to feed 60 cows.

According to the AFS-model, automation reduces the daily time necessary to feed dairy herds. AFS enabled automatic mixing and delivery of rations without the presence of a working person. In this modelling, the working time requirement consisted of the loading time, the preparation/closing time and the time for controlling the feeding distribution. The working time needed for feeding a herd size of 60 cows amounted to 12.9 MPmin day^{-1}, reducing working time by half an hour compared with the CFS. The time for feeding 120 cows was 16.0 MPmin day^{-1}. For 180 and 240 cows the working time requirement consisted of 22.3 and 28.5 MPmin day^{-1}, respectively (Figure 3).

Pezzuolo *et al.* (2016) calculated the working time requirement of the operation time (working time requirement without consideration of preparation and transit time) also reported a significant reduction from 2.5 h day^{-1} (CFS) to 1.02 h day^{-1} (AFS). Their study included 90 cows receiving a diet based on four components. Additionally, they investigated economic correlations and found decrease in the costs for preparing and distributing the ration. They calculated daily costs of 1.44 EUR (m^3)$^{-1}$ TMR and 0.16 EUR cow^{-1} for the CFS and costs of 0.91 EUR (m^3)$^{-1}$ TMR and 0.10 EUR cow^{-1} for the AFS.

Finally, according to our assumptions, a nearly 70% decrease in daily feeding time could be expected by using an AFS compared with a CFS.

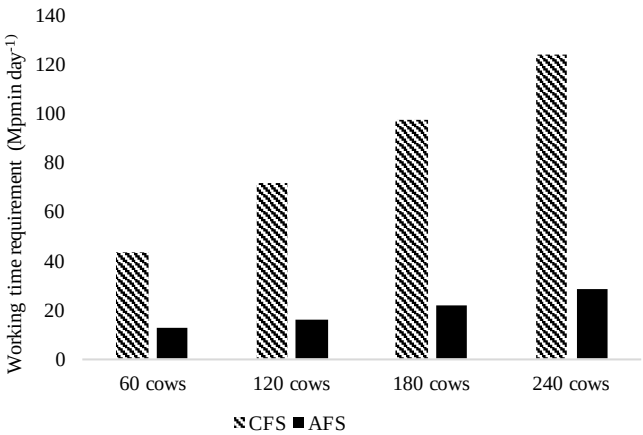

Figure 3. Daily working time requirement for feeding cows by a conventional (CFS) or by an automatic feeding system (AFS)

Figure 4 shows the daily working time requirement per cow being negatively correlated with herd size. In the present modelling, the daily and cow-related working time requirement for feeding cows by a CFS ranged between 0.73 MPmin (60 cows) and 0.52 MPmin (240 cows). The AFS-model indicated also reduced values in dependence on the cow number. With 0.22 MPmin (cow and day)$^{-1}$, the greatest effect could be observed in the herd of 60

cows. Because the factors influencing working time were equal in the modelled variants, the effects were comparatively low in larger herds, with values between 0.13 MPmin (cow and day)$^{-1}$ and 0.12 MPmin (cow and day)$^{-1}$. Herd size, in particular, is an important factor determining feeding technology (Gargiulo *et al.,* 2018). Increasing the capacity of the feed mixer wagon would be beneficial to save time and reduce workload. Nevertheless, the calculation system is able to provide information being tailored to the needs of its users.

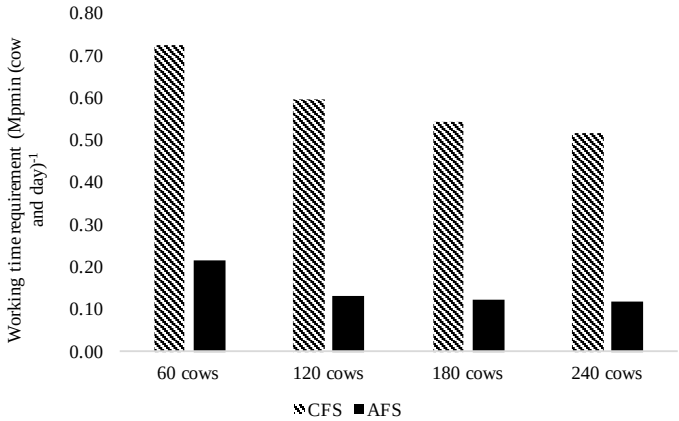

Figure 4. Daily working time requirement per cow for feeding cows by a conventional (CFS) or by an automatic feeding system (AFS)

Conclusions

Models consisting of specific influencing factors and working conditions were developed to calculate the working time requirement. Results of the present modelling indicated that AFS as an example of automation in dairy farms led to a lower working time requirement compared with CFS. Thus, automatic systems provide opportunities, not only for improvements of individual animal management, but also for saving working time and increasing flexibility. The calculation system is useful to combine single work processes as well as to analyse complex systems. It can be worthwhile to calculate and to compare working methods, to evaluate future developments and to optimise work processes and conditions.

References

Auernhammer, H. (1976). *Eine integrierte Methode zur Arbeitszeitanalyse, Planzeiterstellung und Modellkalkulation landwirtschaftlicher Arbeiten, dargestellt an verschiedenen Arbeitsverfahren der Bullenmast*, Landwirtschaftsverlag, Münster-Hiltrup, Germany, 261 pp.

Boehlje, M. and Schiek, W. (1998). Critical success factors in a competitive dairy market. *Journal of Dairy Science,* 81: 1753–1761.

Da Borso, F., Chiumenti, A., Sigura, M. and Pezzuolo, A. (2017). Influence of automatic feeding systems on design and management of dairy farms. *Journal of Agricultural Engineering,* 48(1): 48–52.

Gargiulo, J.I., Eastwood, C.R., Garcia, S.C. and Lyons, N.A. (2018). Dairy farmers with larger herd sizes adopt more precision dairy technologies. *Journal of Dairy Science,* 101(6): 5466–5473.

Gindele, E.H. (1972). *Die Bedeutung agrarstruktureller Elemente für eine rationelle Arbeitserledigung in der Feldwirtschaft*, Landwirtschaftsverlag, Münster-Hiltrup, Germany, 203 pp.

Kanawaty, G. (1992). *Introduction to work study*, International Labour Office, Geneva, Switzerland, 291 pp.

Pierpaoli, E., Carlia, G., Pignattia, E. and Canavari (2013). Drivers of Precision Agriculture Technologies Adoption: A Literature Review. *Procedia Technology,* 8: 61–69.

Reith, S., Frisch, J. and Winkler, B. (2017). Revision of the Working Time Classification to Optimize Work Processes in Modern Agriculture. *Chemical Engineering Transactions,* 58: 121–126.

Reith, S. and Hoy, S. (2018). Review: Behavioral signs of estrus and the potential of fully automated systems for detection of estrus in dairy cattle. *Animal,* 12(2): 398–407.

Schingoethe, D.J. (2017). *A 100-Year Review:* Total mixed ration feeding of dairy cows. *Journal of Dairy Science,* 100(12): 10143–10150.

Šístkova, M., Pšenka, M., Kaplan, V., Potěšil, J. and Černín, J. (2015). The effect of individual components of total mixed ration (TMR) on precision dosing to mixer feeder wagons. *Journal of Microbiology, Biotechnolgy and Food Sciences,* 5(1): 60–63.

Calving prediction from video: Exploiting behavioural information relevant to calving signs in Japanese black beef cows

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Abstract

Behavioural information relevant to calving is extracted and exploited successfully for automatic calving prediction from videos. Calving prediction is key for preventing fatal accidents such as stillbirth and dystocia. Such a prediction has been performed using contact sensors to capture a cow's typical movements before calving. However, directly attaching sensors to a cow's body is not desirable from the viewpoint of animal welfare, economic load, and safety for livestock farmers. This paper presents a camera-based, noncontact calving prediction system that captures typical precalving movements such as rotations, turns and step-backs. The information on the frequency of such behaviours and that on the frequency of changes in the behaviours are extracted every few minutes using deep neural networks and used as inputs to a calving predictor based on support vector machines. Experimental comparisons conducted using the videos of four Japanese black beef cows of normal and precalving statuses demonstrated that the system developed with five cows' videos achieved a precision rate of 97% and a recall rate of 82% for a cow that was active before calving.

Keywords: deep neural network, calving prediction, behavioural features, precision livestock farming

Introduction

Calving prediction is critical for enabling cattle farmers to prevent fatal accidents during calving, such as stillbirth and dystocia. It is widely known that specific "precalving" signals are observed from clinical signs and behavioural changes of cows. It is important to precisely capture the signals before calving occurs such that cattle farmers can assist the cows on site to avoid accidents.

Most of the existing calving prediction systems are based on information obtained from *contact* sensors. For example, Gyuonkei (Sakatani *et al.,* 2018) is a temperature sensor that monitors a cow's vaginal temperature that starts to decrease before calving. Agrimonitor (Barrier *et al.,* 2012) is an abdominal harness that detects the contractions of a cow's uterine and abdomen as another precalving event. Alert'VEL (Krieger *et al.,* 2018) uses an accelerometer to detect the frequency increase in cattle tailing that typically occurs before calving. Finally, RumiWatch (Zenher *et al.,* 2018) is a noseband sensor-based calving prediction system that detects a decrease in the frequency of rumination and feeding.

Although contact-sensor-based calving prediction systems are currently utilised by many cattle farmers, they present some practical problems: *(i)* high monetary cost for installation, and *(ii)* high labour cost for farmers when equipping cows with sensor devices. Meanwhile, *noncontact*-sensor-based approaches such as using cameras can overcome these problems; however, few studies have yet proposed approaches for calving prediction using only camera images (Cangar *et al.,* 2008; Sumi *et al.,* 2017). Although Canger *et al.* and Sumi *et al.* have classified cows' behavioural states such as 'standing or lying' and 'moving or not', these states are not always relevant to calving signs. In addition, some previous works indicated that walking motions increased at the precalving status (Jensen, 2012; Saint-Dizier *et al.,* 2015).

The present study therefore introduces precalving behaviours with focus on walking motions that are observable from videos (e.g. standing, sitting, rotation, turn, step-forward and step-backward), and exploits such behavioural information to develop a calving prediction system. Here, the frequency of behaviours and changes in behaviours are examined.

The proposed calving prediction system is composed of two stages: a behavioural feature extractor built with a deep neural network (DNN) that classifies a cow's behaviours observable in videos, and a calving sign detector that determines whether the cow's status is precalving or normal. Accurate features extracted in the preceding stage can contribute to reliable prediction even when the latter calving detector is trained with fewer data. In addition, the outputs of the first-stage behaviour classifier can help farmers judge whether the prediction results are correct.

To demonstrate the effectiveness of the proposed system, experimental comparisons were conducted using video datasets collected from a camera installed in a farm. The knowledge obtained from the present study may be useful in designing features that are suitable for calving sign detection from videos.

Material and methods

Cow's behaviours related to calving signs

A cow's walking time generally increases in a calving day (Saint-Dizier *et al.,* 2015). Hence, the present study focuses on a cow's walking behaviours as the calving signs. From monitoring five cows, it is found that the cows' behaviours are composed of the following:

Standing: a cow is standing on a spot;

Sitting: a cow is sitting or lying down;

Rotation: a cow is rotating with a front leg as a pivot;

Turn: a cow is walking forward while changing directions;

Step-forward: a cow is walking forward without changing directions;

Step-back: a cow is walking backward.

For the five cows, the appearance frequency of the aforementioned behaviours was investigated every hour from six hours before to immediately before calving. Figure 1 shows the result for one cow. This result indicates that characteristic behaviours can be observed from four hours before calving, and their frequencies increase, especially from three hours before calving. In the present study, therefore, a precalving status is defined as the period from three hours before to immediately before calving.

Calving prediction system

The developed calving prediction system is composed of two stages: a behavioural feature extractor and a calving sign detector. In the first stage, the DNN extracts the information of the cows' behaviours related to the calving signs. Subsequently, a support vector machine (SVMs; Hearst *et al.,* 1998) at the latter stage determines whether the cow's status is precalving or normal using the behavioural features extracted in the preceding stage. As the behavioural features the statistics on the appearance frequency of characteristic behaviours and change frequency in these behaviours are accumulated for a few minutes.

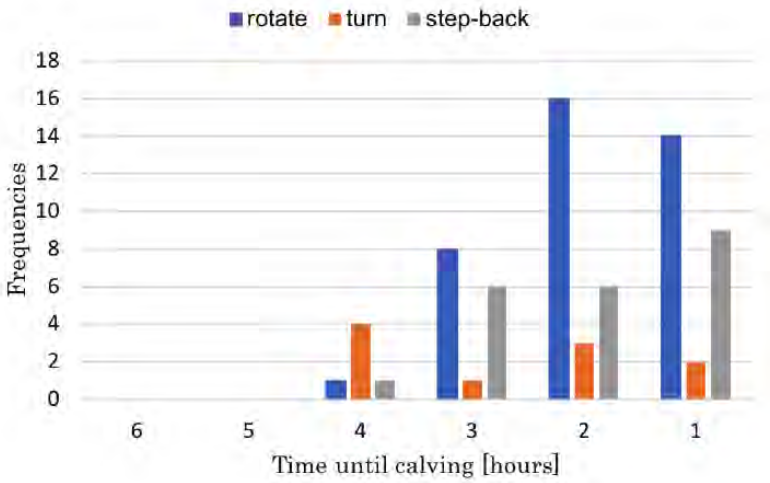

Figure 1. Frequencies of cows' behaviours (calving time: 11:34 AM on 4 June 2017)

DNN-based behaviour classifier used for feature extraction

As a behavioural feature extractor, a behaviour classifier is constructed using a five-layered fully connected DNN that classifies three classes of behaviours, i.e. standing, sitting, and walking. The 'walking' class includes behaviours such as rotation, turn, step-forward and step-back. A cow's region is detected from video frames by YOLOv3 (Redmon *et al.*, 2018). Figure 2 shows an example of detecting a cow using YOLOv3. The target cow can be tracked using the intersection over union of a cow's regions across video frames.

Figure 2. Example of cow detection using YOLOv3

Figure 3 shows an overview of the behavioural feature extractor. Here, the width and height of the bounding box yielded by YOLOv3 and the movement of the centre of the bounding box (four dimensions in total) were concatenated over 21 video frames, yielding an 84-dimensional vector that was used as an input to the five-layered DNN. This 84-dimensional vector was extracted every five seconds. The numbers of three hidden-layer units in the DNN are 600, 256, and 150. The number of units in the output layer is three.

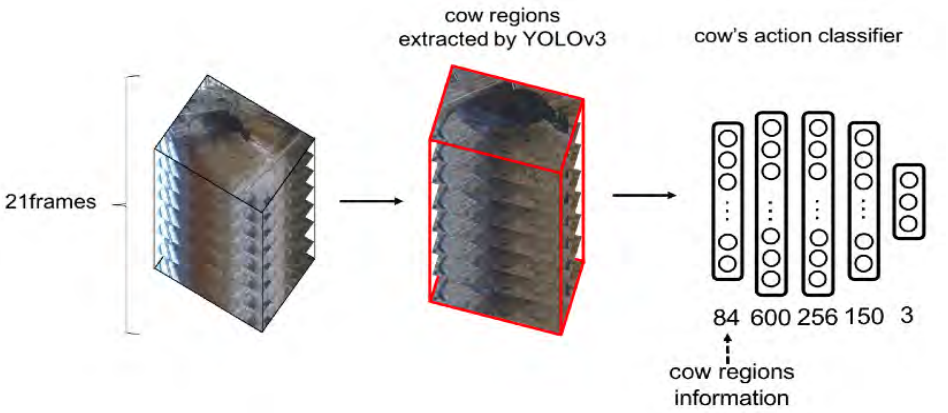

Figure 3. Network architecture of cow's behaviour classifier. Four-dimensional cow's region features are concatenated over 21 frames and used as inputs to DNN

Behavioural features

The present study examines two behavioural features: the appearance frequency of behavioural components and the change frequency of the behaviours. These features can be obtained from the aforementioned DNN.

Frequency of behavioural components

Cows tend to walk around in a chamber as calving approaches. In this case, the frequency of standing and sitting is expected to be high in a normal status. In contrast, the frequency of walking should be high in a precalving status. Under this assumption, the appearance frequency of the characteristic behaviours may be effective in determining whether the cow's status is precalving or normal. The hidden layer outputs (HLOs) in the first-stage DNN are assumed to represent a type of behavioural component information, and its statistics accumulated for a period can represent the appearance frequency of such behavioural components. In the present study, third-layer HLOs are exploited as the behavioural features and used as inputs to the subsequent SVM-based calving sign detector. Here, the HLOs were averaged over 20 samples. As the HLOs are obtained every five seconds, the resulting feature vector contained two-minute information.

Frequency of behavioural changes

Walking in a calving chamber indicates changes in a cow's behaviours. The M-measure (Hermansky *et al.*, 2013; Ogawa *et al.*, 2016) was introduced to capture the amount of such behavioural changes during a period. The M-measure accumulates the divergence of behavioural changes during a period. It is defined as

$$\mathbf{M(\Delta t)} = \frac{1}{\mathbf{T-\Delta t}} \sum_{t=\Delta t}^{T} \mathbf{D(p_{t-\Delta t},,p_t)}\,, \tag{1}$$

where Δt denotes the time interval between behaviour posterior probabilities at $t-\Delta t$ and t, and $D(\mathbf{p},\mathbf{q})$ denotes a symmetric Kullback-Leiber (KL) divergence between behaviour posteriors

$$D(\mathbf{p},\mathbf{q}) = \sum_{k=0}^{K} p^{(k)} \log\frac{p^{(k)}}{q^{(k)}} + \sum_{k=0}^{K} q^{(k)} \log\frac{q^{(k)}}{p^{(k)}} \tag{2}$$

where $p^{(k)}$ is the k-th element of the posterior probability vector $\mathbf{p}\in R^K$. Because the cows move less in a normal status, the posterior probability of standing or sitting is primarily high. This implies that $M(\Delta t)$ remains low regardless of Δt. In contrast, because the cows

move around before calving, the cows' behaviours change frequently. This indicates that M(Δt) tends to be high, and that the M-measure is effective in determining whether the cow is in a normal or precalving status. Figure 4 shows the average and standard deviation of the M-measure values calculated from the video of a cow, as a function of Δt. Figure 4 shows that the M-measure patterns are distinctive between the normal and precalving statuses. The following M-measure pattern, therefore, is exploited as a behavioural feature.

$$M=[M(1),M(2),\ldots,M(20)] \qquad (3)$$

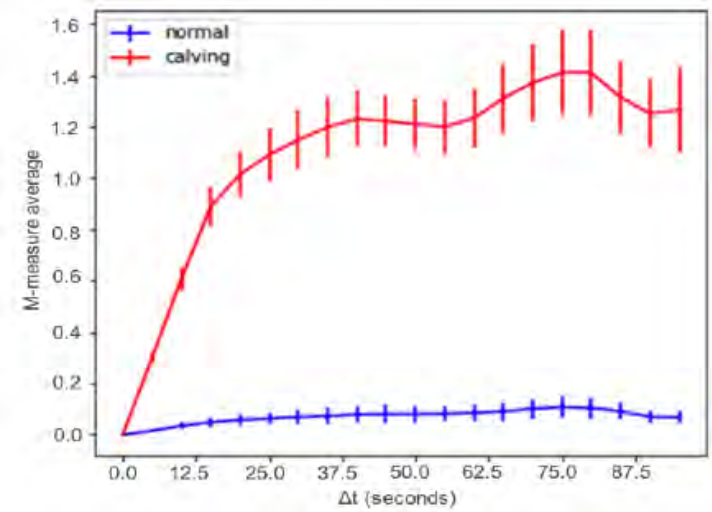

Figure 4. M-measure values as a function of . A cow walked during precalving in this example

Video materials and experimental setting

Videos of ten Japanese black beef cows were recorded in a calving chamber in a ranch in Kagoshima, Japan, from May to December in 2017. This video was sampled at one frame per second. Based on preliminary investigations, the period from 27–24 h before calving is defined as the normal status, and that from three hours to immediately before calving is defined as the precalving status. Tables 1 and 2 list the details of the training data for the SVM-based calving sign detector and testing data, respectively. Note that the cows included in the training data are different from those included in the testing data. The cow detector and DNN-based behavioural feature extractor were trained on other training datasets.

Table 1. Periods of collecting training data. All data were collected in 2017

Cow index	Normal status	Precalving status
Train-1	05/27 22:00 - 05/28 00:59	05/28 23:00 - 05/29 00:59
Train-2	06/02 06:00 - 08:59	06/03 06:00 - 08:59
Train-3	06/24 02:00 - 04:59	06/25 02:00 - 04:59
Train-4	07/12 23:00 - 07/13 01:59	07/13 23:00 - 07/14 01:59
Train-5	11/07 11:00 - 13:59	11/08 11:00 - 13:59

Table 2. Periods of collecting testing data. Numbers in parenthesis are number of feature vectors extracted during corresponding period. All data were collected in 2017

Cow index	Normal status	Precalving status
Test-1	06/14 05:30 - 08:29 (56)	06/15 05:30 - 08:29 (96)
Test-2	08/30 12:00 - 14:59 (39)	08/31 12:00 - 14:59 (38)
Test-3	09/29 21:00 - 23:59 (83)	09/30 21:00 - 23:59 (73)
Test-4	10/23 02:00 - 04:59 (83)	10/24 02:00 - 04:59 (80)
Test-5	11/23 07:00 - 09:59 (46)	11/24 07:00 - 09:59 (43)

Results and discussion

Experimental comparisons were conducted to demonstrate the effectiveness of the developed system. This system inputs a video clip of 21 s (21 video frames as: t-10,⋯,t,⋯,t+10) to yield a behavioural feature vector. In this experiment, the performance of detecting calving signs was evaluated for behavioural features extracted every five seconds. Specifically, regarding the third cow for testing (Test-3) listed in Table 2, 83 normal status feature vectors and 73 precalving status feature vectors were used as inputs to the calving predictor, and those inputs were evaluated to verify if they were correctly identified. The difference in the number of extracted feature vectors among the cows for testing was due to cow detection errors.

Table 3 lists the precision, recall, and f-measure for the precalving status for each individual cow of the testing data. The two features of HLO and M-measure patterns were evaluated. The second cow (Test-2) was excluded from the testing because the typical behaviours did not appear at precalving, i.e. it did not move even before calving. It was observed that the third cow walked around for more than two hours in the precalving status, thus yielding a high calving detection performance. In contrast, other cows tended to repeat walking and rest for a long period. If the duration of rest is long during the precalving period, such a period can be identified as a normal status. In this case, behavioural features do not contribute to calving sign detection.

Table 3. Evaluation result for testing data. All values are for precalving status. Numbers in parenthesis express number of samples (each extracted from a video clip of 21 s) evaluated

Cow index (# samples)	Feature	Precision	Recall	f-measure
Test-1 (152)	HLO ave	0.83	0.41	0.55
	m-measure	0.73	0.40	0.52
Test-3 (156)	HLO ave	0.95	0.81	0.87
	m-measure	0.97	0.82	0.89
Test-4 (163)	HLO ave	0.54	0.28	0.36
	m-measure	0.74	0.36	0.49
Test-5 (89)	HLO ave	0.64	0.86	0.73
	m-measure	0.57	0.91	0.70

Conclusions

Calving sign detection systems using behavioural features relevant to calving signs were developed in this study. Two behavioural features were examined: one represented the frequency of behavioural components and the other represented the behavioural changes. The former was obtained as the hidden layer output in the DNN and the latter was obtained as the M-measure pattern. Experimental comparisons using the videos of four Japanese black beef cows demonstrated that the developed system trained on five-cow videos yielded a precision rate of 97% and a recall rate of 82% for a cow that was active before calving. For future studies, both the feature extractor and calving detector will be improved to explicitly cope with time-series information.

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References

Barrier, A., Haskell, M., Macrae, A., and Dwyer, C. (2012). Parturition progress and behaviours in dairy cows with calving difficulty, *Applied Animal Behaviour Science,* 139: 209–217.

Cangar, O., Leroy, T., Guarino, M., Vranken, E., Fallon, R., Lenehan, J., Mee, J., and Berckmans, D. (2008). Automatic real-time monitoring of locomotion and posture behavior of pregnant cows prior to calving using online image analysis, *Computers and Electronics in Agriculture,* 64: 53–60.

Hearst, M. A, Dumais, S. T, Osuna, E., Platt, J., and Scholkopf, B. (1998). Support vector machines, *IEEE Intelligent Systems and their Applications,* 13: 18–28.

Hermansky, H., Variani, E., Peddinti, V. (2013). Mean temporal distance: Predicting ASR error from temporal properties of speech signal, *2013 IEEE International Conference on Acoustics, Speech and Signal Processing*, pp.7423–7426.

Jensen, M.B. (2012). Behaviour around the time of calving in dairy cows, *Applied Animal Behaviour Science,* 139: 195–202.

Krieger, S., Sattlecker, G., Kickinger, F., Auer, W., Drillich, M., and Iwersen, M. (2018). Prediction of calving in dairy cows using a tail-mounted tri-axial accelerometer: A pilot study, *Biosystems Engineering,* 173: 79–84.

Ogawa, T., Mallidi, H., Dupoux, E., Cohen, J., Feldman, N., Hermansky, H. (2016). A new efficient measure for accuracy prediction and its application to multistream-based unsupervised adaptation, *23rd International Conference on Pattern Recognition*, pp.2222–2227.

Redmon, J., and Farhadi, A. (2018). YOLOv3: An Incremental Improvement, *arXiv*, arXiv:1804.02767.

Saint-Dizier, M., and Chastant-Maillart, S. (2015). Methods and on-farm devices to predict calving time in cattle, *The Veterinary Journal* 205: 349–356.

Sakatani, M., Sugano, T., Higo, A., Naotsuka, K., Hojo, T., Gessei, S., Uehara, H., and Takenouchi, N. (2018). Vaginal temperature measurement by a wireless sensor for predicting the onset of calving in Japanese Black cows, *Theriogenology* 111: 19–24.

Sumi, K., Kobayashi, I., Hori, Y. (2017). A study on cow monitoring system for calving process, in Proc. *IEEE 6th Global Conference on Consumer Electronics*, pp.381–382.

Zehner, N., Niederhauser, J., Schick, M., and Umstatter, C. (2018). Development and validation of a predictive model for calving time based on sensor measurements of ingestive behavior in dairy cows, *Computers and Electronics in Agriculture.*

Two-stage calving prediction system: Exploiting state-based information relevant to calving signs in Japanese black beef cows

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Abstract

A two-stage calving sign detection system is proposed to effectively use state information on the calving behavior of Japanese black beef cows (e.g. standing or sitting, tail raising). Automatic calving sign detection from cameras can help livestock farmers prevent fatal accidents to calves during calving. The following requirements were identified for such camera-based detection systems: 1) ability to work with a small volume of data (because calving events are not very frequent), 2) robustness to changing environments, and 3) ability to explain the reasons for the prediction results. However, these requirements are not realistic for end-to-end approaches such as the predictions using a single deep neural network (DNN). This study presents a two-stage calving prediction system, in which calving-relevant information obtained using a DNN-based feature extractor is used as the input for another DNN-based calving sign detector. The first-stage DNN extracts discriminative features of typical pre-calving behaviour in cows, such as increased lying time and tail raising. The former DNN is expected to achieve accurate feature extraction and to enable training of the latter DNN using small-scale data. Furthermore, the states observable from the video frames, which are outputs of the former DNN, can make use of the crowdsourcing for sustainable growth; moreover, these states can also provide the basis for the accurate prediction of calving. Experimental comparisons conducted using video scenes of five cows during the normal and pre-calving states demonstrated that the proposed system achieved a calving precision rate of 81% and a calving recall rate of 91%.

Keywords: deep neural network, image recognition, beef cows, calving prediction

Introduction

Livestock farmers generally provide childbirth assistance to cows in order to prevent fatal accidents to calves during calving. To enable such assistance, many devices that automatically detect the pre-calving behaviours of cows and alert the farmers have been examined (Rutten *et al.*, 2015; Marchesi *et al.*, 2013; Sakatani *et al.*, 2018; Krieger *et al.*, 2018). These devices are mainly contact sensors that detect characteristic changes in cows before calving. For example, a fall in the vaginal temperature is detected by a temperature sensor (e.g. Gyuonkei, http://www.gyuonkei.jp), uterine and abdominal contractions are detected using an abdominal harness (e.g. AGRIMONITOR, http://www.agrimonitor.be), and the increase in the number of times the tail rises can be detected by an accelerometer (e.g. Alert'VEL, http://www.albinnovation.com/alertvel). However, such contact sensors are generally expensive and sometimes dangerous to both cows and farmers when being mounted. Therefore, it is desirable to predict calving using images obtained from cameras, which are non-contact sensors, for human- as well as cow-friendly monitoring of the process; yet few studies have reported the detection of calving signs using a camera (Cootes *et al.*, 1995; Sumi *et al.*, 2017).

The following requirements have been identified for a system deploying such camera-based detection: 1) ability to work with a small volume of data (because calving events are not very frequent), 2) robustness to changing environments, and 3) ability to explain

the reasons for its prediction results. The first point is important for anomaly detection in general, where events occur rarely and look significantly different from the majority of the data. The calving prediction system therefore needs be designed taking into account that calving is not a frequent event. The second point can be considered as a special precaution while using images. Since the background information on the cows' images is different at each farm, it is necessary to design a system that is robust against changes in the surrounding environment. These two points are important to introduce a pattern recognition technology to support the livestock industry without large-scale open datasets. The third point is important for helping the farmers understand the reasons for the alert. This can be considered as the advantage of using image information because it is easy to confirm the basis of the judgement made by the system.

An end-to-end approach with a single deep neural network (DNN) has attracted global attention as a necessary technique in various applications because it can significantly simplify complicated pattern recognition systems. However, the end-to-end approach cannot satisfy all the above-mentioned requirements, since learning both the feature extraction and the detection functions through a single network generally requires a large volume of data. Judging the calving signs from the images can be done only by experts including livestock farmers, spending a considerable amount of time to accumulate the labelled data necessary for system deployment (a barrier to requirement (1)). Furthermore, this approach is also not capable of adaptively improving the system to cope with the changing environments (a barrier to requirement (2)); and, since the system becomes a black box in an end-to-end approach, it is difficult to provide the basis for its predictions (a barrier to requirement (3)).

In the present study, a two-stage calving prediction system has been designed to satisfy all the above requirements. In the proposed system, information related to the calving signs of cows is extracted from images using convolutional neural networks (CNNs), and a fully connected neural network subsequently predicts an imminent calving by using the extracted features (as shown in Figure 1). Note that the design of the feature extractor (i.e. first-stage neural network) becomes a key to satisfying the abovementioned requirements. In the feature extractor, calving-relevant information based on the observable states of the cows such as tail rising (Jensen, 2012; Bueno *et al.*, 1981) is extracted in the form of intermediate outputs from the CNNs. Thus, by explicitly extracting the features related to the calving signs, a highly reliable detector can be built even with a small volume of calving data (requirement (1)). Since the observable states can be judged by non-experts, crowdsourced annotation is possible. This leads to the possibility of an early and efficient operation of the system, even if the installation environment of the camera changes (requirement (2)). In addition, since the feature extractor outputs posterior probability of the cows' state to the input image, the proposed system can explain the basis for its prediction results based on the frequency of the cows' states (requirement (3)).

To demonstrate the effectiveness of the developed system, experimental comparisons were conducted using video scenes of five Japanese black beef cows collected from a camera installed in a farm. The knowledge obtained from the present experiments may be useful in developing calving sign detection systems from videos.

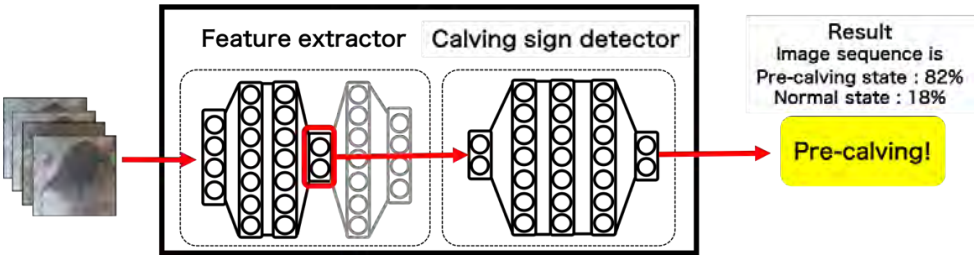


Figure 1. Schematic diagram of two-stage calving prediction. Information on pre-calving is extracted from image sequence and used as input for calving sign detector

Material and methods

Cows' states related to calving signs

The present study focuses on the following two states observable from the images:

- Switching between standing and sitting postures
  - » Increase in the number of posture changes, e.g. switching between standing and sitting posture, around two to six hours before calving (Saint-Dizier & Chastant-Maillard, 2015; Jensen, 2012) and the increase in sitting time two hours before calving (Jensen, 2012).
- Tail raising
  - » Increase in the number of the tail rising around four to six hours before calving (Jensen, 2012), and elevation in the position of the tail before calving (Bueno *et al.*, 1981).

Examples of these two states are shown in Figure 2. There have been several investigations on the changes in clinical and behavioural states of pre-calving cows in livestock science, and these were also observed in the videos collected for the purpose of this study. Note that these characteristic states can be captured by cameras and judged even by non-experts in animal husbandry and breeding.

Calving prediction system

The developed system is composed of two stages: a feature extractor and a calving sign detector. In the first stage, the CNNs extract the information of the states of cows related to calving signs (e.g. standing or sitting, tail raising). Then, a fully connected neural network at the latter stage determines whether it is a pre-calving state or a normal state by using the information extracted from the CNNs of the preceding stage. In this case, the CNNs function as a feature extractor and are constructed to identify the states of cows that are strongly related to calving signs.

(a) Sitting

(a) Tail raising

Figure 2. Pre-calving behaviour of cows targeted in this study

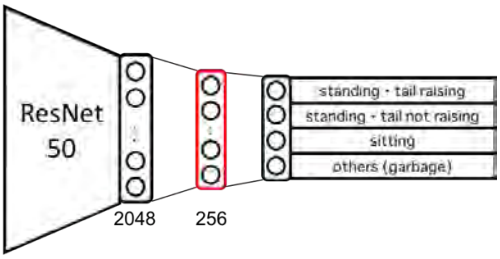


Figure 3. Network structure of feature extractor. Intermediate outputs can be expected to contain information relevant to calving signs

Stage 1. Feature extractor

The feature extractor comprises CNNs that classify the given images of the cows into the following four classes: (1) standing cow with a raised tail, (2) standing cow without a raised tail, (3) sitting cow, and (4) garbage (others). The garbage class includes images in which the calving state of the cows cannot be judged (e.g. no cows, calf, and noisy images). The convolution layer has the same structure as ResNet 50 (He *et al.*, 2016), followed by 256 units of a fully connected layer, and the output layer yields the posterior probabilities of the aforementioned four classes. The network structure of the feature extractor is shown in Figure 3.

As a preliminary experiment, the performance of the cows' state classification was investigated. The evaluation data were manually annotated by the authors, and large-scale training data were annotated through crowdsourcing. Then, the labels of the training data were checked and corrected by the authors. Amazon Mechanical Turk (https://www.mturk.com) was used as the crowdsourcing platform and the classification accuracy was found to be 69.6%. The intermediate layer output of this CNN is expected to contain information that is effective for a classification of the relevant state of the cows. In this case, the statistics of the intermediate layer outputs that are accumulated for a period are considered to represent the frequency information of the element that determines the state of the cows; this frequency information is considered to be suitable as a pre-calving feature because the identified state is related to the calving signs. In the present study, the output of the fully connected layer with 256 units is used as an input to a subsequent calving sign detector.

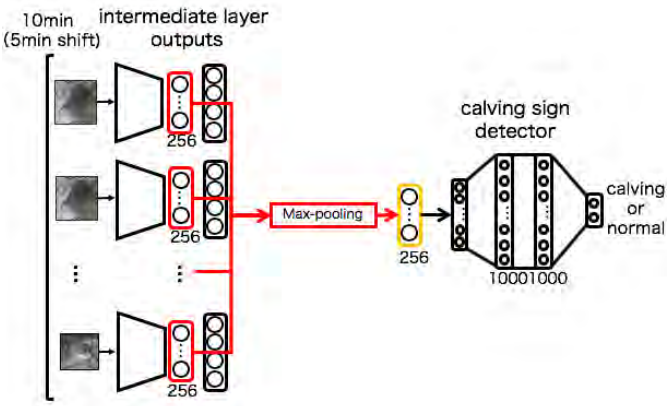


Figure 4. Extraction of features relevant to calving and structure of calving sign detector

Stage 2. Calving sign detector

The schematic diagram of the calving-relevant feature extraction and calving sign detection is illustrated in Figure 4. The latter system is constructed using a fully connected neural network that identifies pre-calving signs. Here, max-pooling across temporal frames is applied to the extracted calving-relevant features. It should be noted that the max-pooling in the proposed system selects a maximum value for each dimension of the 256-dimensional feature vectors extracted from image sequences of ten-minute videos. This calving sign detector consists of 1,000 units of two fully connected layers and uses ReLU (Nair & Hinton, 2010) as the activation function. In the proposed and developed system, pre-calving signs are detected from the image sequences of a certain length of time. In this case, the max-pooling of the intermediate layer outputs is conducted every five minutes for the input image sequences of ten minutes (at most 600 images).

Experimental data

Japanese black beef cows close to calving were constantly monitored via a camera mounted on a chamber. Figure 5 shows an image of two cows in the chamber observed obliquely from above. The data used for the calving prediction experiments include ten different calving scenes collected from a farm in Kagoshima, Japan, from May to December in 2017. Here, the video scenes with a cow that has calved were sampled every one second. The detail of the training data for the calving prediction system is listed in Table 1 and that of the evaluation data is listed in Table 2. The training and evaluation data include five calving scenes, respectively. In this experiment, the normal state is defined as the state 27–24 hours before calving, and the pre-calving state is defined as the state three to zero hours before calving. Note that there are no overlaps between this data and the data used for the training of the feature extractor.

Figure 5. Example of recorded image. Two Japanese beef cows are in chamber

Experimental setup

The precision, recall, and area under the curve (AUC) of the calving status were calculated. The cows' regions were detected by YOLOv[3] (Redmon & Farhadi, 2018), resized to 224 × 224, and used as the input to the feature extractor. During training of the neural networks for the feature extractor and subsequent calving sign detector, a stochastic gradient descent method was carried out with a learning rate of 0.01. A minibatch size was 20.

Table 1. Periods of collecting training data. All data were collected in 2017

Index	Normal state	Pre-calving state
1	05/27 22:00 - 05/28 00:59	05/28 23:00 - 05/29 00:59
2	06/02 06:00 - 08:59	06/03 06:00 - 08:59
3	06/25 02:00 - 04:59	06/26 02:00 - 04:59
4	07/12 23:00 - 07/13 01:59	07/13 23:00 - 07/14 01:59
5	11/07 11:00 - 13:59	11/08 11:00 - 13:59

Table 2. Periods of collecting evaluation data. Number of samples taken as input to calving sign detector is shown in parentheses. All data were collected in 2017

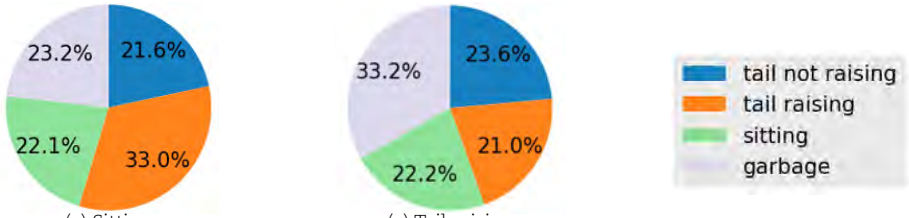
Index	Normal state	Pre-calving state
1	06/14 05:30 - 08:29 (25)	06/15 05:30 - 08:29 (34)
2	08/30 12:00 - 14:59 (34)	08/31 12:00 - 14:59 (28)
3	09/29 21:00 - 23:59 (36)	09/30 21:00 - 23:59 (36)
4	10/23 02:00 - 04:59 (36)	10/24 02:00 - 04:59 (36)
5	11/23 07:00 - 09:59 (33)	11/24 07:00 - 09:59 (30)

Results and discussion

The precision, recall, and AUC values for each individual cow and total value for all the five cows in the evaluation data are presented in Table 3. The results show that an AUC of 0.85 or more was obtained for each individual cow and all the five cows in the evaluation data, indicating that the discrimination between a pre-calving status and a normal status by the proposed system performed well with smaller data. In addition, Figure 6 shows the average posterior probabilities of the outputs of the feature extractor over ten minutes when predicting a pre-calving status and a normal status correctly. The average posterior probability of tail raising before calving is 12% higher than usual. Thus, the feature extractor captures the increase in the number of tail rising instances before calving. This is expected to explain the basis for the prediction to the farmers by presenting the cows' state and the frequency of each state while detecting pre-calving signs based on this posterior probability.

Table 3. Precision, recall, AUC values calculated using pre-calving as positive case for each individual cow and all five cows in evaluation data

Index	Precision	Recall	AUC
1	0.72	1.00	0.85
2	0.81	0.75	0.82
3	1.00	0.97	1.00
4	0.79	0.86	0.90
5	0.78	0.93	0.95
All	0.81	0.91	0.91



(a) Sitting (a) Tail raising

Figure 6. Posterior probabilities of feature extractor outputs averaged over ten minutes for correctly predicted samples in evaluation data

Conclusions

Three requirements for designing a calving prediction system using videos from a camera was defined and satisfied to develop such system. The proposed two-stage calving prediction system, in which calving-relevant information obtained from a CNN-based feature extractor is used as the input for another fully connected neural network-based calving sign detector, achieved a calving precision of 0.81 and a calving recall of 0.91. In this system, the time-series information is lost by simply max-pooling the intermediate layer outputs obtained from the image sequences. For our future investigations, the system will be extended to handle time-series information regarding the cows' pre-calving behavior.

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References

Bueno, L., Tainturier, D. and Ruckebusch, Y. (1981). Detection of parturition in cow and mare by a useful warning system. *Theriogenology*, 16: 599–605.

Cootes, T.F., Taylor, C.J., Cooper, D.H. and Graham, J. (1995). Active Shape Models - Their Training and Application. *Computer Vision and Image Understanding*, 61: 38–59.

He, K., Zhang, X., Ren, S. and Sun J (2016). Deep Residual Learning for Image Recognition. In: *Proc. The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, US, pp. 770–778.

Jensen, M.B. (2012). Behaviour around the time of calving in dairy cow. *Applied Animal Behaviour Science,* 139: 195–202.

Krieger, S., Sattlecker, G., Kickinger, F., Auer, W., Drillich, M. and Iwersen, M. (2018). Prediction of calving in dairy cows using a tail-mounted tri-axial accelerometer: A pilot study. *Biosystems Engineering,* 173: 79–84.

Marchesi, G., Leonardi, S., Tangorra, F.M., Calcante, A., Beretta, E., Pofcher, E. and Lazzari, M. (2013). Evaluation of an electronic system for automatic calving detection on a dairy farm. *Animal Production Science,* 53: 1112–1114.

Nair, V. and Hinton, G.E. (2010). Rectified linear units improve restricted boltzmann machines. In: *Proc. The International Conference on Machine Learning (ICML)*, Israel, pp. 807–814.

Redmon, J. and Farhadi, A. (2018). YOLOv3: An Incremental Improvement. *arXiv*.

Rutten, C.J., Steeneveld, W., Kamphuis, C., Huijps, K. and Hogeveen, H. (2015). The potential of using sensor data to predict the moment of calving for dairy cows. *Precision livestock farming applications*, 161–167.

Saint-Dizier, M. and Chastant-Maillard, S. (2015). Methods and on-farm devices to predict calving time in cattle. *The Veterinary Journal*, 205: 349–356.

Sakatani, M., Sugano, T., Higo, A., Naotsuka, K., Hojo, T., Gessei, S., Uehara, H. and Takenouchi, N. (2018). Vaginal temperature measurement by a wireless sensor for predicting the onset of calving in Japanese Black cows. *Theriogenology,* 111: 19–24.

Sumi, K., Zin, T., Kobayashi, I., and Hori Y. (2017). A study on cow monitoring system for calving process. In: *Proc. 2017 IEEE 6th Global Conference on Consumer Electronics*, *Japan*, pp. 381–382.

TrackLab 2: a new solution for automatic recording of location, activity and social behaviour of group-housed animals

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Abstract

The popularity of precision livestock farming is largely driven by a desire to optimise productivity, profitability and comfort. At the same time, there are growing societal concerns about animal welfare and animal health in relation to food safety and human health. These concerns can be addressed by academic and applied research into animal welfare and health indicators and increasingly by the utilisation of welfare and health metrics in operational farm management systems. TrackLab 2 is the latest tool for the measurement of livestock welfare and health indicators. It is designed to integrate and process multi-modal data for the capture of welfare and health indicators such as social behaviour, place-preference, activity, feeding and physiology. It was beta tested on four sites in the dairy cattle, poultry and pig farming domain. These first explorative tests revealed that TrackLab metrics are useful for both scientific, applied and commercial livestock research. TrackLab hardware is working well for large animals (cows, calves, pigs, sheep, poultry) but needs to be optimised for use on young birds and piglets. TrackLab 2 is also the first version to be applied in the operational farming context. The utilisation of welfare and health metrics in the operational context, to a level that exceeds the productivity focus, can prove a valuable asset in addressing societal concerns and enhancing livestock farming sustainability.

Keywords: TrackLab, livestock, welfare, health, monitoring, multi-modal

Introduction

With the trend towards larger group housing systems in farm animals, it becomes increasingly important to be able to monitor the behaviour, performance and welfare of individual animals housed in groups. Traditional methods, such as live and video-based observation and behavioural scoring, are difficult and time-consuming. Automated observation using video tracking is a powerful and versatile technique for detailed analysis of movement and behaviour of single animals, dyadic interactions or small groups. However, video tracking falls short when the number of animals to be monitored is large, and it does not work in large scale and outdoor environments. For large indoor spaces, ultra-wideband (UWB) radio tracking offers a robust and accurate alternative to video tracking: it offers real-time individual tracking of large numbers of animals (e.g. 100 animals or more), at a high spatial accuracy (up to 15 cm), in large areas (e.g. 60 × 40 m), with a high sampling rate (e.g. 1 Hz). In the field, GPS tracking is the technique of choice, with the latest chip sets offering positioning accuracies of around 2 m, and local networks, enabling long-range data communication in areas where there are no cellular networks. However, the sensors alone do not make a solution for the livestock researcher or the livestock industry. That requires a suitable software package for experiment design, data acquisition, storage, visualization and analysis. Together with the sensors and data processing hardware, it should provide a seamlessly integrated end-to-end solution for livestock research and R&D in the livestock industry.

Here we present TrackLab 2, a new software package and integrated system for the acquisition and analysis of location, activity and social behaviour of group-housed animals. It is the successor of TrackLab 1, which has been on the market since 2013 and which has been used in a wide variety of livestock research projects on cattle, pigs, poultry and sheep (Frondelius *et al.*, 2014, Van Mil *et al.*, 2015, Stadig *et al.*, 2016, Rodenburg *et al.*, 2017, De Haas *et al.*, 2017).

Solution description

TrackLab is designed to support livestock research in academic institutes (health, welfare and environment focus), breeding and genetics, veterinary research (in biocontainment facilities) as well as livestock research for the development of animal nutrition and pharma. It is important to identify the differences in objectives and workflow in these application fields if you want to establish a versatile and broadly deployable solution. TrackLab 2 offers several functional and technical innovations relative to its predecessor:

System architecture and tracking technology

TrackLab 2 has a distributed and scalable client-server architecture, supporting multiple concurrent users and measurements at multiple locations. The TrackLab solution is designed for three types of livestock monitoring environments: Indoor tracking in barn environments, indoor tracking in biocontainment labs and outdoor tracking in feedlots and pastures. The indoor tracking solution uses both Angle-of-Arrival (AoA) and Time-Difference-of-Arrival (TDoA) techniques through wall-mounted sensors that use ultra wideband (UWB) radio communication to determine the location of the animals. The accuracy achieved with UWB-based localization (up to 15cm) allows for analysis of behaviour classes (e.g. social behaviour, accurate place-preference and activity statistics) that cannot be achieved with other positioning techniques (e.g. RFID, WiFi). The system hardware is suitable for use in BSL-3 with the sensors (IP65) and tags (IP69k) suitable to withstand commonly used sterilization methods.

The outdoor tracking system is based on GPS localization and, depending on the conditions (weather, blocking objects), can achieve an accuracy of around 2 m. The tag contains a solar panel to make it self-contained if applied in sunny regions, and with possibilities of applying a bigger battery in cloudy regions. The tag stores data locally and sends it in batches through a local LoRa data communication network. One antenna can receive data from within a radius of 2 - 10 km depending the geographical features.

Hardware: animal solutions

The TrackLab tracking hardware is compatible with the most common livestock animals. The indoor tracking solution comes with tag solutions for cows and horses (collar-based), sheep and goats (harness-based), poultry (backpack-based) and pigs (eartag-based). The outdoor tracking solution supports application on cows and horses (collar-based) as well as small ruminants (sheep and goats - harness-based). Each tag solution is designed and tested to be robust enough to endure high impact stress (e.g. cattle barns) and hostile environments where sterilization procedures are applied (e.g. biocontainment labs) or where low temperatures and high humidity occur (outdoor environments). The tag solutions for poultry and pigs are designed and tested to be light enough and to have a good ergonomical fit to prevent animal discomfort.

Analysis: raw data playback & export

The TrackLab software is based on a 'white box' concept: transparency is given on the logic and algorithms, and both raw data (coordinates) and derived measures can be exported for further analysis in other applications. Track data and aligned raw behavioral

measurement data can be played back (at different speeds) to enhance behavioral insights and to inspect contextual circumstances that may explain data outliers (Figure 1).

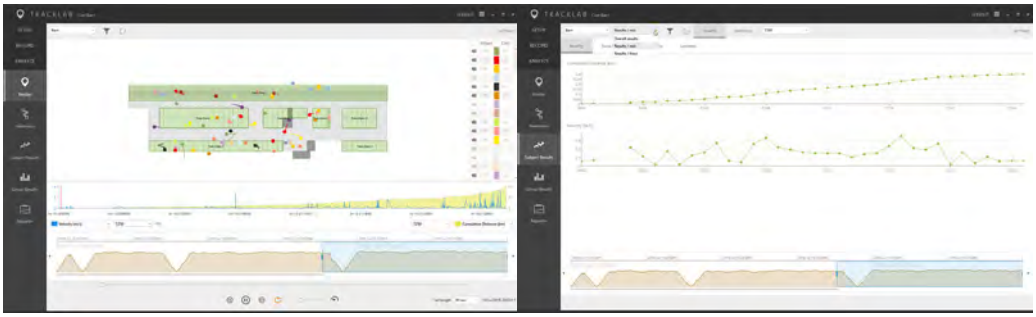

Figure 1. The data replay window (l) and statistics results per user-selectable timebin

Analysis: activity

Animal activity can be used as an indicator of animal health (e.g. as lameness indicator) or estrous behaviour (Roelofs & van Erp-van der Kooij, 2015). TrackLab has three different types of activity measurements available: distance moved, velocity and velocity-based movement categories, based on user-defined velocity thresholds.

Analysis: place-preference (+ indirect feeding, drinking)

Place-preference analysis is valuable for gathering various welfare-related insights (e.g. bedding preference investigations), insights into the efficiency of barn infrastructure layouts but can also be used as an indirect cue for eating and drinking behaviour (frequencies and time spend at the drinking trough or feed alley). It has also been used to measure the response and attention to new objects, such as new feed types or play objects, or it can be used to analyse the location-dependency of certain behaviours.

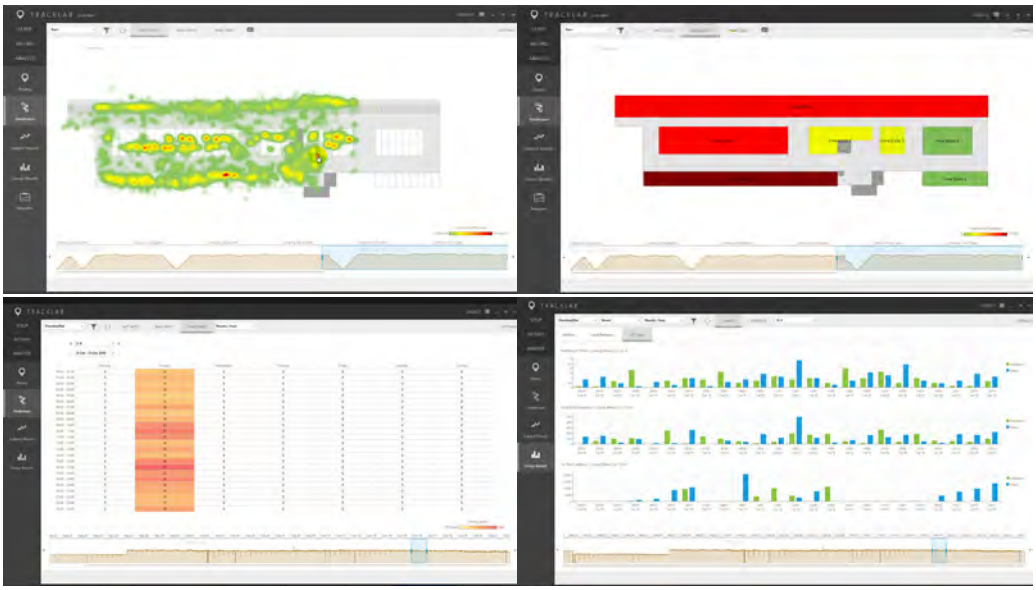

Figure 2. Qualitative heatmap (top left), areas of interest heatmap (top right), timetable heatmap (bottom left) and area visit statistics

Analysis: social behaviour

Social behaviour in cattle is receiving increasing interest from the research community. Insights in social behaviour can inform us about the effect of the hierarchy of a herd on overt aggression within the group. As sharing resources may be facilitated by social stability, aggression may have a negative effect on feeding of submissive cows and thus the productivity of the herd as a whole. Also, normal social development is assumed to have a positive effect on animal welfare. TrackLab 2 offers two types of social behaviour analysis: basic proximity analysis (Figure 3), which calculates the frequencies and time spent in proximity to any other animal, and social network analysis, which provides insight into the pair relations within the group.

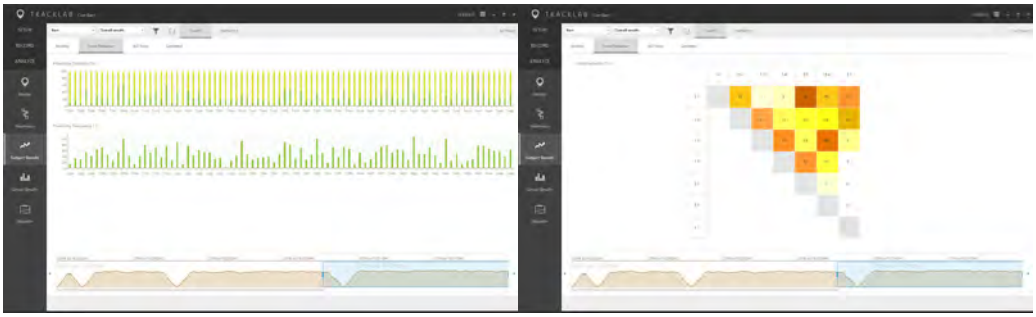

Figure 3. Social behaviour – proximity statistics (l) and pair relations (r)

Analysis: feeding behaviour

Besides the previously described indirect measurement of feeding and drinking based on animal presence in a feeding alley or near a drinking trough, accelerometer-based sensor technologies provide a means to measure these behaviours directly on the animal. The aim is to quantify durations and frequencies of eating versus rumination.

Analysis: posture and gait

Basic activity indicators such as standing and walking and movement states can be reliably detected with tracking technologies. Lying can theoretically also be detected with UWB localization techniques, however, it requires adjusting and extending the UWB sensor configuration. Accelerometry provides a more cost-effective and proven application for the measurement of lying, standing and walking (Munksgaard *et al.*, 2006; Trénel *et al.*, 2009). Moreover, todays accelerometers are often combined with other sensors such as magnetometers, gyroscope and/or altimeter. Combining the output of these sensors with machine learning techniques allows us to detect a broader range of behaviour nuances (e.g. lameness, head butts and mounting in cattle, pecking or jumping in poultry or aggression in pigs), with higher reliability.

Analysis: welfare metrics

In prototyping efforts, special interest goes out to welfare indicators such as related to agonistic behaviour (e.g. head butts, displacement, chasing or fighting), as described in the Welfare Quality® assessment protocol for cattle (Welfare Quality®, 2009), established by the Welfare Quality® Consortium. As opposed to the previously described social behaviour indicators proximity and pair relations, the challenge here is to identify the aggressor from the submissive animal; a received head-butt shows only a subtly different pattern in accelerometer data compared with an applied head butt.

First experiences in practice (beta tests)

Application in the dairy cattle domain

TrackLab 2 was installed on two dairy cattle sites: the Dairy Campus in Leeuwarden and Aeres Farms in Dronten, both in The Netherlands. At Aeres Farms, TrackLab 2 was installed in a high-tech dairy cattle unit. Over 55 dairy cows have been equipped with UWB tags and data are being collected for several months during the winter period. The cows in this high tech unit are being monitored with a variety of different sensors to study their production, health and welfare continuously. Aeres Farms is a practical farm connected to the Aeres University of Applied Sciences in which students, under the supervision of researchers, learn how to optimally manage dairy cattle. An important aspect is not only how to interpret the outcome of automated monitoring systems already available on the market but also what is behind the warning or alert of these systems. Students learn by doing observational studies how these systems work, what validity and reliability mean and what makes a system both sensitive and specific. The TrackLab 2 system at Aeres Farms has contributed to both a better understanding of how sensors can be applied in practice by the future generation farmers, and has given insights into how the cows use the facilities. Aeres Farms and the research unit are especially interested in individual differences between cows regarding the distance travelled daily and how it relates to cow factors (stage of lactation), health and welfare; which places in the facilities are preferred and which are avoided; and if there is a variation between cows for time spent at the feeding path, the water units and the lying areas. For all these questions it is assumed that there is large variation between animals, but sound scientific evidence is lacking. The next step is to relate these outcomes to productivity, health and welfare measures in order to optimise herd management.

Application in the poultry domain

UWB tracking and TrackLab have been applied in the PhenoLab project at Wageningen University, funded by Breed4Food. The aim of the project was to provide a proof of principle for automatic tracking of location, activity and proximity of individual laying hens when housed in a group. A test room at Wageningen University was equipped with the TrackLab system, as well as with the EthoVision XT video tracking system. In the first phase of the project, activity measurements measured with both systems was compared. Individual hens were equipped with the UWB tag in a backpack and placed in the PhenoLab. The recorded distance moved was very similar between both systems (Rodenburg *et al.*, 2017). In the second phase, we investigated if we could reproduce known line differences in activity using the PhenoLab. To meet this aim, we compared birds from a highly active line selected for high feather pecking (HFP) with birds from a low feather pecking line (LFP) or an unselected control line. As expected, HFP birds showed much higher activity levels in the PhenoLab than birds from the other two lines. Interestingly, within the HFP line, birds that had actually been observed to perform high levels of feather pecking in the home pen were much more active than victims of feather pecking from the same line (Rodenburg *et al.*, 2017). De Haas *et al.* (2017) also showed that feather peckers spent less time in close proximity compared with controls. One challenge with UWB in poultry is the relatively high weight of the tags (approximately 30 g). This means that the method cannot be used to track birds lighter than approximately 500 g. We are currently investigating the combination of UWB tracking with passive RFID tracking. For passive RFID tracking, the tags can be much lighter as they do not contain a battery. To conclude, for adult poultry, the UWB system offers perspective for application in research and allows automatic recording of activity and location. For younger birds, passive RFID tracking systems may be more suitable.

Application in the pig farming domain

An example of how TrackLab is applied not only in research but also in farming practice, is The Family Pig project ("Het Familievarken"). An innovative pig farm was built, designed to keep pigs in a natural environment (social context and enriched), thus avoiding stress and illness. TrackLab is used to measure animal proximities in support of an individualized feeding system, to measure the presence of pigs in a 'pig toilet' (in support of toilet flushing, thereby separating urine from faeces and reducing emission of methane and nitrous oxide as a result). This is a good example of TrackLab, by origin a research tool, can be utilised for improvement of animal welfare, health and the environment (antibiotics and emissions reduction), in an operational farming context.

Relevance of livestock research to the farming practice

Several research initiatives focus on so-called Precision Livestock Farming (PLF), which is driven by the increasing application of sensor technologies on-farm. Remarkably, projects on Precision Livestock Research are scarce and this is particularly true for the fields of animal welfare and animal behaviour. The majority of studies focusing on farm animal welfare still rely on visual observation for data collection, and therefore the frequency and duration of assessments and the number of animals observed are restricted. Because of the lack of practical tools to monitor behaviour, most farmers are not aware of the relevance of behaviour for their everyday decisions and due to the lack of demand and complexity of behaviour, suppliers of farm automation hardly develop tools in this area. Tools for automated monitoring of behaviour, if available, would enable much more accurate estimation of effects of treatments (e.g. housing conditions, feeding regimes) in scientific studies and thus contribute to our understanding of the impact of such factors on animal behaviour. Moreover, effects of interventions, whenever abnormal values of behavioural parameters are detected, can be investigated with automated monitoring tools. If such interventions show clear benefits, it is likely that farmers will be interested to implement such tools in their farm management. As with most other sensor applications, the combination of tracking data with other sensor data, e.g. from accelerometers, will improve the interpretation of abnormal values and application of appropriate measures.

Conclusions

The TrackLab 2 solution was successfully probed in explorative tests in the dairy cattle, poultry and pig behaviour domain. First experiences with version 2 reveal that it can be useful not only for scientific research but also for the applied livestock sciences. Moreover, for the first time, TrackLab was utilised in an operational (pig) farming context where its behaviour analysis output (e.g. subject proximities, area visits) was used as input for individualized feeding and toilet systems, designed to improve animal welfare, productivity and emissions reduction. On the tracking hardware side, we can conclude that the system is compatible with farm conditions (e.g. humidity, low temperature) and that it works well on larger animals (cows, cattle, pigs, adult chicken, sheep) but that it needs to be optimised (lighter, smaller) to be suitable for young birds and piglets as well.

Discussion

We hope that TrackLab 2 will contribute to livestock research (behavioural phenotyping, testing different diets, welfare and health monitoring) and increasingly to precision livestock farming as well (monitoring individual animal health and welfare and enhancing housing and management systems). Societal concern over food safety, the health and welfare of livestock animals and the environment may pose an existential risk to the livestock farming industry. Metrics for animal health and welfare do not only give valuable insight for livestock researchers; there is great potential in utilising these metrics in the

operational farming context. This combination can prove a valuable asset that can help the livestock industry to remain sustainable towards the future.

References

De Haas, E.N., van der Eijk, J.A.J., van Mil, B., Rodenburg, T.B. (2017). Phenolab: ultra-wide band tracking shows feather-pecking hens spent less time in close proximity compared to controls. In *Proceedings of the 51st Congress of the International Society for Applied Ethology*. Aarhus, Denmark.

Frondelius, L., Pastell, M., Mononen, J. (2014). Validation of the TrackLab Positioning System in a Cow Barn Environment. *Proceedings of Measuring Behavior 2014* (Wageningen, The Netherlands, August 27-29, 2014).

Munksgaard, L., Reenen, C.G., Boyce, R. (2006). Automatic monitoring of lying, standing and walking behavior in dairy cattle. *Journal of Animal Science,* 84(Suppl.): 304.

Rodenburg, T.B., van der Eijk, J.A.J., Pichová1, K., van Mil, B., de Haas, E.N. (2017). PhenoLab: automatic recording of location, activity and proximity in group-housed laying hens. In *Precision Livestock Farming '17*. Nantes, France.

Roelofs, J.B., van Erp-van der Kooij, E (2015). Estrus detection tools and their applicability in cattle: recent and perspectival situation HAS University of Applied Sciences, Den Bosch, The Netherlands in *Animal reproduction,* 12(3): 498–504.

Trénel, P., Jensen, M.B., Decker, E.L., Skjøth, F. (2009). Technical note: Quantifying and characterizing behavior in dairy calves using the IceTag automatic recording device. *Journal of Dairy Science,* 92: 3397–3401.

Van Mil, B., Frondelius, L., Spink, A.J., Pastell, M., Mononen, J., Noldus, L.P.J.J. (2015). Accurate tracking of cows in a barn environment using TrackLab. *Proceedings Second Dairy Care Conference* (Cordoba, Spain, 3-4 March 2015), p.48.

Welfare Quality® (2009). *Welfare Quality® Assessment Protocol for Cattle*. Welfare Quality® Consortium, Lelystad, Netherlands.

Het Familievarken. Retrieved from http://www.hetfamilievarken.nl/.

Adaption of data-intensive monitoring and tracking systems in outdoor pig production for better decision making – literature review and project idea

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Abstract

In this paper, we are trying to give a detailed overview of the results of the research on the behaviour and production parameters of pigs kept outdoors, as well as the Information Technology (IT) monitoring methods used so far in commercial, intensive, largescale pig farms. A more detailed overview of the literature on the research of traditional meat products is also part of our work. This literature review is the basis to examine the adaptability of monitoring systems to free-range conditions, providing a basis for developing a tracking system for Mangalica and Iberian pigs. In our planned project we intend to adapt IT-methods and procedures to free-range pigs for offering an easy to handle, cost-efficient, useful IT-devices for monitor Mangalica and Iberian pigs, a possibility for gathering behavioural information about their pig herds and indirect data on the health status and production parameters of pigs. Changing the daily rhythm, detecting the deviation immediately makes it possible to detect and treat the sick, possibly infectious animals. By evaluating the data collected by the sensors, the farmer can get a comprehensive picture of the pigs kept outdoors without disturbing the animals. The data can be inserted into the production process of traditional products, so the premium quality associated with free-range pigs can be verified. With this adapted technology, it is possible to achieve precision pig keeping under free-range conditions. Traceability and transparency of free range pig production system would be realised and 'labelled product' would be controlled from farm to fork relations.

Keywords: Mangalica, iberian pigs, blockchain, RFID, outdoor, tracebility, traditional meat products

Objectives

We present a project idea submitted to an H2020 call which is under review. We present the results of the literature that were relevant to the project idea, as well as our objectives and expected results. In conventional indoor pig housing IT solutions have already been developed to successfully evaluate animal behaviour and/or production parameters. We intend to adapt these methods and procedures to free-range pigs to provide easy to handle, cost-efficient and useful IT-devices for monitoring pigs. This will give farmers the possibility to gather behavioural information about their pig herds, as well as other indirect data on the health status and production parameters. This will be achieved using passive and active RFID chips and wireless stations to detect the pigs by locating individual members of pasture stock and observing their daily rhythm. Changes to the daily rhythm of an animal will be immediately detected as a deviation from the average behaviour of this individual and also from the average behaviour of other individuals, making the detection and treating of sick, possibly infectious, animals faster. The time spent at the feeder gives the farmer information on food consumption, and changes in drinking water consumption can be symptom of a disease. By evaluating the data collected by the sensors, the farmer can get a comprehensive picture of the pigs kept outdoors without disturbing the animals. The data can be inserted into the production process of pork products, so the premium quality associated with free-range pigs can be verified. In the framework of the project, the

aim is to monitor Mangalica and Iberian pigs. We make personalized recommendations for the design of the IT system for different sizes of farms. With individual identification and tracking of pigs, traceability and transparency of the production system would be realised and 'labelled products' would be controlled from farm to fork relations.

Material and methods

In the conception of our project, we have defined four sub-goals. After a thorough literature survey, it is clear that the use of relevant IT technologies is extensively applied in recent research, however, the literature is concerned mostly with indoor pig farming and very few literature sources were found concerning IT solutions applied in the case of free range pigs. The most probable reason is that deploying technologies is much easier in a smaller and better controllable space than in a larger, outdoor area, as the outdoor IT devices are exposed to weather conditions wich may cause degradation in performance. The justification of our project is proved by this fact. There are lots of applications of IT in the case of other farm animals kept on pasture such as cattle, sheep and goats. The IT solutions applied for these animals can only be used in a small part in the case of pigs. The main reason is their different behavioural habits. Pigs use grassland primarily as a living space, not as a feed source. In the case of pigs, behaviours that determine animal welfare are not observed in these types of farm animals (rooting, wallowing). In addition, pigs live in a serious social relationship, and their breeding and social habits differ significantly from other animals. A further challenge is the individual marking of pigs, so that they can be permanently and remotely identified. Pigs are not as comfortable with wearing gadgets or widgets, e.g. a collar, that are easily applicable for cows, goats or sheep. Our project is also looking for solutions to track the health condition of the pigs. During the project we will develop a platform for free range and mainly for organic pig farmers, for gathering behavioural and production data from their organic pig system, with adapting already existing IT solutions applied in indoor keeping systems. This IT system gathers real-time data from RFID devices (mostly passive and several active) about the location of pigs without their unnecessary disturbance. With individual identification of pigs, traceability and transparency of outdoor production system would be realised and 'labelled product'-life would be controlled from farm to fork relations.

Literature review

Behavioural aspects

In outdoor systems, at a reduced level of supplementary feed, a higher frequency of rooting occurs. These results suggest that it is possible, through management measures like allocation of new land, feeding strategy and movement of housing and feeding facilities, to have a stratified cultivation of and nutrient load on the land. Andresen *et al.* (2001) demonstrated that rooting could replace a mechanical treatment and even result in a higher yield of the following crop. Laister and Kondrad (2005) investigated the following behavioural categories in intensive breeds of growing-finishing pigs in an outdoor system: feeding, drinking, exploring, resting, comfort behaviour, locomotion, playing, agonistic and eliminative behaviour. On warm days, feral pigs rest in sunny places and clearings of a pine tree forest, whereas on hot days the pigs search for cool and shadowy places in a high forest (Meynhardt, 1988). Pigs are exploratory animals that spend a considerable amount of time moving between parts of the enclosure and examining distant and close habitats (Stolba & Wood-Gush, 1989). According to Ingold & Kunz (1997), moist and wet places stimulate rooting. The most important patterns of comfort behaviour in pigs are rubbing and wallowing, the latter fulfilling two purposes: firstly, the mud bath shall free the pigs from ectoparasites and itches and, secondly, it contributes to the animals' thermoregulation (Zerboni & Grauvogl, 1984). In Johnson *et al.* (2001), investigating behaviour found that

outdoor sows were more active. Johnson *et al.* (2003) found that outdoor reared pigs spent more time walking and playing compared to indoor reared pigs.

Production performance aspects

Reproductive performance: The genetic background for pigs in organic production in Sweden is the same as in conventional pig production (Wallenbeck *et al.*, 2008). In the organic herds, the total number of piglets born per litter and the number of piglets stillborn per litter were higher than in the conventional herds. Crushing of the piglets by the sow during the first days of life has been reported to be a more common cause of death in organic herds (Wallenbeck, 2009). Longer nursing period in the organic system means longer recovery period. It has to be shown to be beneficial for the reproductive performance. This might reflect larger variations among the organic herds in housing and management (Lindgren *et al.*, 2013). Number of litter per sow was lowest in the organic system, partly because of a longer weaning period and partly because of poorer reproduction results. Larsen & Jorgensen (2002) found that poor production results are not related to the fact that sows are kept outside but, probably, are related to the longer lactation period. Lindgren *et al.* (2013) related the lower number of weaned piglets per litter to the opportunity for movement of the sows that result in inadequate nursing and weakening of the piglets as well as crushing by the sow.

Growth performance: According to Danielsen *et al.* (2000), organic feeding and access to an outdoor run led to a higher proportion of ham muscles in the carcass. These results are much in line with those of Miller *et al.* (2003) who found that organic farming led to a higher muscle and back fat thickness. In the summer period, a feed conversion comparable to indoor conditions was obtained in some investigations (Sather *et al.*, 1997), whereas in other periods of the year or in other investigations, a higher feed consumption per kg gain has been reported (Stern *et al.*, 2002; Sather *et al.*; 1997). Hermansen (2005) found that restricted intake in outdoor systems kept pigs under 80 kg live weight followed by *ad lib* indoor. It resulted in a feed conversion rate comparable to indoor feeding and overall daily gain was only reduced by 10 - 15% compared to *ad lib* feed indoor. Laister & Kondrad (2005) investigated behaviour, performance and carcass quality of growing-finishing pigs from three intensive breeds in outdoor circumstances. Weissmann *et al.* (2005) investigated performance, carcass and meat quality of different pig genotypes in an extensive outdoor fattening system on grass clover in organic farming. They calculated feed conversion ratio over all fattening pigs as the total amount of feed in relation to the total amount of body weight gain. Farke & Sundrum (2005) investigated growth performance and carcass yield in outdoor fattening system offering grazing possibilities. Their results show that it is possible to obtain acceptable daily live-weight gains and carcass yields in organic pig production under free range conditions. In their opinion, further studies are needed to estimate the amount of 'herbage on demand' and feed intake of crops by pigs in outdoor conditions. Growth performance of pigs in outdoor production system can be affected by climatic conditions. Honeyman & Harmon (2003) found that during the winter, outdoor pigs require higher energy to keep warm than during the summer, resulting in a slower growth rate. Rodríguez-Estévez *et al.* (2011) investigated average daily gain of Iberian fattening pigs when grazing natural resources. The traditional finishing system of the Iberian pig is linked to the 'dehesa' (Quercus sp. open woodlands), in order to use the abundance of food provided by acorn ripening (called montanera), when pigs only eat grass and fallen acorns (Rodríguez-Estévez *et al.*, 2009a).

Social aspects

Rural areas in the EU member states are more dependent on agriculture as a source of income and employment, with opportunities for gainful employment in the non-farm

rural economy relatively scarce (Davidova *et al.*, 2013). To boost competitiveness and profitability, the EU seeks to stimulate enhanced value-added production, drawing on its reputation for quality goods (European Parliament and The Council of European Union, 2012). One potencial type of quality goods are Traditional Food Products (TFPs). A traditional food may be classified as: 'a product… made accurately in a specific way according to the gastronomic heritage, … and known because of its sensory properties and associated with certain local area, region or country' (Guerrero *et al.*, 2009). These goods generally possess positive images due to superior taste, nostalgia and/or ethnocentrism (Almli *et al.*, 2011; Vanhonacker *et al.*, 2010). Balogh *et al.* (2016) addresses this central question, building on recent advances in Willingness to Pay (WTP) methodologies, which are applied to an exemplary case of a TFP, namely, the Hungarian Mangalica salami. Mangalica salami is an ideal product for exploring Willingness To Pay for Traditional Food Products as the main motivation for its purchase in Hungary is its indigenous origin and heritage. The Mangalica breed does not possess any protected status at European level but there is coordination at the domestic level via the National Association of Mangalica Breeders (NAMB). The NAMB certifies Mangalica pigs, officially guaranteeing the origin of genuine Mangalica products (Balogh *et al.*, 2016). Certification is important for increasing the customer base as inexperienced consumers and those who have relatively weaker preferences for the good place with greater emphasis on quality certification. Unfortunately, many quality labels possess inadequate regulatory systems (European Court of Auditors, 2011), resulting from inexperience and limited resources. Thus, here is a consequent need to share experiences between successful TFPs, commanding substantial premiums and possessing robust regulatory systems, and those less well developed. In the case of Iberian pigs breeders, Iberian Acorn meat (especially ham) is a very demanded and well considered TFP, and it is subject to very strict regulations to get quality certifications and category labels.

Internet of Things (IoT) monitoring system at field

To achieve high efficiency, productivity, and performance of a precision farm business, the IT infrastructure and IT services have to be robust and reliable. The state of the art key issues along the complete data workflow, i.e. data collection, data storage, data analysis, and data visualization, can be found in Wolfert *et al.* (2017). At present, most of the systems of Ordoñez-García (2017), Bhargava (2016), Dholu (2018) are conceptionaly designed into three layers: data collection, data analysis and processing, and presentation. As described in Dholu (2018), sensors send data through a gateway to the cloud where it is processed and visualized for smartphones in order to access the agricultural parameter from everywhere. Through the powerful gateway/edge devices more and more data is processed on premise. Edge Mining not only optimises memory usage of the sensor device, but also builds a foundation for future real-time responsiveness of the prototype system in Bhargava (2016). Our project idea approach goal is to effectively design robust IoT applications that require a tradeoff between cloud- and local edge-based computing, depending on dynamic application requirements. Data fusion, as described in Rui (2012), is one of the most basic approaches that performs data reduction, e.g. by merging the redundant data that emerges from the neighbouring sensor nodes. Light-weight data mining algorithms are developed to optimise sensor readings, optimise RFID zone detection and enable real-time detection of important events. There are a number of specialized pig farm management systems, like nedap, CLAAS, Cloudfarms or SwineManagement.com, but all of them do not monitor the welfare of an individual pig.

Certified pig-pork supply chain for the customer

The integration of chain partners in innovation process enhances the capacity to innovate and reduces the risks involved in implementing innovation (Earle, 1997; Gellynck & Kühne,

2008; Pittaway *et al.*, 2004). The agri-business sector is characterised by a large number of micro, small and medium sized enterprises (SMEs) and as a low-tech industry. This applies for the traditional food sector in particular. Only few studies are published that focus particularly on innovations in TFPs (Jordana, 2000). Feasible applications relate to improving the production process in order to assure quality and traceability (Gellynck & Kühne, 2008). For the successful introduction of innovations in TFPs, it is also important to have a good understanding of customers' perceptions, expectations and attitudes towards traditional food products and of consumers' attitudes towards innovations in TFPs (Linnemann, Benner, Ververk & van Boekel, 2006). Current progress towards automated detection of health and welfare compromises indicates the three categories of approaches to automation are emerging. The first category reports only on detecting behaviours using sensors (with RFID, video or other sensors). The next category applies the detection method over time, records behavioural data and presents these to staff for monitoring of potential problems, typically in graph form (e.g. on mobile phone). This enables identification of behavioural changes, but requires farm staff to identify the change. The third category automatically analyses the recorded behaviour over time to detect behavioural changes and automatically sends alerts to staff advising them of behavioural changes and potential identification of the compromise and rectification (Matthews *et al.*, 2016). For the third category, the data analysis methods were capable of automatically detecting behavioural changes in drinking behaviour from water flow sensors before diarrhoea (Madsen & Kristensen, 2005), in feeding visits and consumption with RFID feeding stations before tail biting (Wallenbeck & Keeling, 2013) and movement activity from video before clinical signs of swine fever (Martinez-Avlés *et al.*, 2015). According to Berckmans (2014) and Tullo *et al.* (2017), precision livestock farming is defined as: the application of process engineering principles and techniques to livestock farming to automatically monitor, model and manage animal production (Tullo *et al.*, 2017). Demands for transparency of traceability of the products and the treatment practices of pigs are increasing from customers who want to be informed about the complete lifecycle of the foot product displayed in a supermarket. In the past, in Europe, this problem was tackled by welfare labelling schemes (e.g. Denmark: DANISH; Netherland: Beter Leven; UK: Red Tractor; Germany: Tierwohl; etc.) define regulatory at each country. These labels stand for compliant farming processes, animal husbandry, meat quality, etc. All of these labels guarantee the compliance of all labelled products but lack the information about the product along the supply chain to the piglet. The EU strategy and many surveys, like Autio *et al.* (2017), are oriented towards considering the development of an instrument to better inform consumers and companies on animal welfare friendly products that could be used by both producers and retailers, ensuring a transparency to consumers without overflowing them with information on the label. The blockchain technology is a promising approach to give transparency, like who was the breeder, how was the pig kept, where was the slaughterhouse, etc. It protocols the pig-pork supply chain. All the important information is put into a blockchain to provide the information to everybody, anytime. A blockchain is a distributed, decentralized data structure that stores transactions transparently, chronologically, and unchangeably in a network. The key players in blockchain market include: IBM, Microsoft, SAP-SE, Ambrosus (Switzerland), Arc-net (UK), OriginTrail, Ripe.io (US), VeChain (China), Provenance (UK), ChainVine (UK), AgriDigital and AgriChain (Australia). The French retailer Carrefour launched a traceability project for its premium farm products in June 2018. Subway and Tyson are testing the FoodLogiQ's (https://www.foodlogiq.com/) blockchain traceability project. Similar to FoodLogiQ is TE-FOOD (https://www.tefoodint.com/), providing a farm to table fresh food traceability ecosystem on blockchain.

Conclusion

Our main goal was to offer and plan an IT system for outdoor pig breeders to help them meet their existing and new challenges like the changing consumption habits require controlled and proven quality. Outdoor pig farming needs more space and results in slower growth but also results in better quality: gives better fat to meat ratio, less diseases, 'happier pigs', etc. On the other hand, some species which are less industrialized (like Mangalica) need other housing conditions. Our proposed idea is to track the animals and to collect and analyse data using IoT technologies in order to inform the farmer and later the consumer as well and to monitor the welfare of the individual pigs. Based on our research and interviews we made with breeders, we decided to use RFID tags and temperature sensors. RFID is a cheap, medium range communication technology, can be used without batteries (passive) to identify the measured pig, and is small enough to integrate into the ear tags. RFID is the optimal solution for tracking pigs (location and movements). Body temperatures and hearth rate of the animals can be used to predict illnesses. Pigs do not like wearable technologies, so we decided to test implantable sensors and automated infrared (non-contact) thermometers / temperature guns as well. Collecting data can help us and the breeders to understand, learn, decide and after collecting enough data to predict events using Machine Learning algorithms. The collected data is stored in a Blockchain database which helps to prove and to certify all the events which occurred during the lifetime of the pigs.

References

Almli, V.L.,, Verbeke, W., Vanhonacker, F., Naes, T., Hersleth, M. (2011). General image and attribute perceptions of traditional food in six European countries. *Food Qual. Prefer.*, 22: 129–138.

Andersen, N., Ciszuk, P., Ohlander, L. (2001). Pigs on grassland - animal growth rate, tillage work and effects in the following winter wheat crop. *Biol. Agric. Hortic.*, 18: 327–343.

Autio, Minna & Autio, Jaakko & Kuismin, Ari & Ramsingh, Brigit & Kylkilahti, Eliisa & Valros, Anna. (2017). *Bringing Farm Animal Welfare to the Consumer's Plate: Transparency, Labelling and Consumer Education*. 10.4324/9781351270045.

Balogh, P., Bekesi, D., Gorton, M., Popp, J., Lengel, P. (2016). Consumer willingness to pay for traditional food products. *Food policy*, 61: 176–184.

Berckmans, D. (2014). Precision Livestock Farming technologies for welfare management in intensive livestock systems. *Rev. Sci. Techn.*, 33: 189–196.

Bhargava, K., Ivanov, S., Donnelly, W. and Kulatunga, C. "*Using Edge Analytics to Improve Data Collection in Precision Dairy Farming*," 2016 IEEE 41st Conference on Local Computer Networks Workshops (LCN Workshops), Dubai, 2016, pp. 137–144.

Danielsen, V., Hansen, L.L., Møller, F., Bejerholm, C. & Nielsen, S. (2000). Production results and sensory meat quality of pigs fed different amounts of concentrate and ad lib clover grass or clover grass silage. In: Hermansen, J.E., Lund, V., Thuen, E. (Eds.). *Ecological Animal Husbandry in the Nordic Countries*, pp 79-86, DARCOF Report No. 2, Tjele, Denmark.

Davidova, S., Bailey, A., Dwyer, J., Erjavec, E., Gorton, M., Thompson, K. (2013). *Semi-Subsistence Farming - Value and Directions of Development Policy Department B: Structural and Cohesion Policies*. European Parliament, Brussels.

Dholu, M. and Ghodinde, K.A. "*Internet of Things (IoT) for Precision Agriculture Application*," 2018 2nd International Conference on Trends in Electronics and Informatics, Tirunelveli, 2018, pp. 339–342.

Earle, M.D. (1997). Innovation in the food industry. *Trends in Food Science & Technology,* 8: 166–175.

European Court of Auditors (2011). *Do the Design and Management of the Geographical Indications Scheme Allow it to be Effective? European Court of Auditors*, Luxembourg.

European Parliament and the Council of the European Union (2012). *Agricultural Product Quality Schemes* (COM/2010) - CF-0423/2010 - 2010/0353 (COD), European Parliament, Brussels.

Farke, A. and Sundrum, A. (2005). Fattening pigs in an outdoor system as a part of the crop rotation within organic farming: Growth performance and carcass yield. In Organic pig production in free range systems. Published as: *Landbauforschung Völkenrode Sonderheft* 281. eds. Sundrum, F. p. 25–30.

Gellynck, X., Kühne, B. (2008). Innovation and collaboration in traditional food chain networks. *J. on Chain and Network Sci.,* 8(2): 121–129.

Guerrero, L., Guárdia, M.D., Xicola, J., Verbeke, W., Vanhonacker, F., Zakowska-Biemans, S., Sajdakowska, M., Sulmont-Rossé, C., Issanchou, S., Contel, M., Scalvedi, M.L., Granli, B.S., Hersleth, M. (2009). *Consumer-driven definition of traditional food products and innovation in traditional foods. A qualitative cross-cultural study*. Appetite, 52: 345–354.

Hermansen, J.E. (2005). Integration of organic pig production into land use. In Organic pig production in free range systems. Published as: *Landbauforschung Völkenrode Sonderheft* 281. eds. F. p. 3–12.

Honeyman, M.S., Harmon, J.D. (2003). Performance of finishing pigs in hoop structures and confinement during winter and summer. *J. Anim. Sci.,* 81: 1663–1670.

Johnson, A.K., Morrow-Tesch, J.L., McGlone, J.J. (2001). Behavior and performance of lactating sows and piglets reared indoors or outdoors. *J. Anim. Sci*., 79: 2571–2579.

Johnson, A.K., McGlone, J.J. (2003). Fender design and insulation of farrowing huts: effects on performance of outdoor sows and piglets. *J. Anim. Sci*., 81: 955–964.

Jordana, J. (2000). Traditional foods: Challenges facing the European food industry. *Food Research International*, 33: 147–152.

Ingold, U., Kunz, P. (1997). Freilandhaltung von Schweinen. Forschungsbericht. Schweizerische Ingenieurschule für Landwirtschaft, Zollikofen. *Landwirtschaftliche Beratungszentrale Lindau*.

Laister, S. and Konrad, S. (2005). Behaviour, performance and carcass quality of three genotypes of growing-finishing pigs in outdoor pig production in Austria: A pilot study. In: *Organic pig production in free range systems*. Edited: Albert Sundrum and Friedrich Weißmann (2005). p.13–19.

Larsen, V.A., Jorgensen, E. (2002). Reproduction performance of outdoor herds. *Livest. Prod.,* 78: 233–243.

Lindgren, Y., Lundeheim, N., Boquist, S., Magnusson, U. (2013). Reproductive performance in pigs reared under organic conditions compared with conventionally reared pigs. *Acta Vet. Scandinavica*., 55: 33.

Linnemann, A.R., Benner, M., Verkerk, R., van Boekel, M.A.J.S. (2006). Consumer-driven food product development. *Trends in Food Science & Technology*, 17(4): 184–190.

Madsen, T.N., Kristensen, A.R. (2005). A model for monitoring the condition of young pigs by their drinking behaviour. *Comp. and Electronics in Agriculture*, 48: 138–154.

Matthews, S.G., Miller, A.L., Clapp, J., Plotz, T., Kyriazakis, J. (2016). Early detection of health and welfare compromise through automated detection of behavioural changes in pigs. *The Vet. Journal*, 217.

Meynhard, H. (1988). *Schwarzwildreport: Mein Leben unter Wildschweinen. 8*. Auflage. Neumann Verlag Leipzig.

Miller, S., Raes, K., Van der Broeck, W., De Smet, S., Janssens, G.P.J. (2003). Performance and meat quality of organically versus conventionally fed and housed pigs from weaning till slauthering. Meat *Sci*., 69: 335–341.

Ordoñez-García, A., Siller, M. and Begovich, O. "*IoT architecture for urban agronomy and precision applications*," 2017 IEEE International Autumn Meeting on Power, Electronics and Computing (ROPEC), Ixtapa, 2017, pp. 1–4.

Pittaway, L., Robertson, M, Munir, K., Denyer, D., Neely, A. (2004). Networking and innovation: A systematic review of the evidence. *Int. J. of Management Reviews*, 5-6(3-4): 137–168.

Rodríguez-Estévez, V., García, A., Peña, F., Gómez, A.G. (2009a). Foraging of Iberian fattening pigs grazing natural pasture in the dehesa. *Livestock Science,* 120: 135–143, ISSN: 1871–1413.

Rodríguez-Estévez, V. (2011). *La encina. La Fertilidad de la Tierra*, 46: 66-69, ISSN: 1576-625X.

Rui, T., Guoliang, X., Benyuan, L., Jianping, W. and Xiaohua, J. Exploiting Data Fusion to Improve the Coverage of Wireless Sensor Networks, *IEEE/ACM Transactions on Networking*, 20(2): 450-462, Apr. 2012.

Sather, A.P., Jones, S.D.M., Schaefer, A.I., Colyn, J., Robertsen, W.M. (1997). Feedlot performance carcass composition and meat quality of free-range reared pigs. Can. *J. Anim. Sci.,* 77: 225–232.

Stern, S., Andresen, N. (2002). Performance, site preferences, foraging and excretory behaviour in relation to feed allowance of growing pigs on pasture. *Livestock Prod. Sci.*, 79: 257–265.

Stolba, A., Wood-Gush, D.G.M. (1989). The behaviour of pigs in a semi-natural environment. *Anim. Prod.*, 48: 419–425.

Tullo, E., Fontana, I., Diana, A., Norton, T., Berckmans, D., Guardino, M. (2017). Application note: labelling, a methodology to develop reliable algorithm in PLF. *Comput. and Electron. Agric.*, 142: 424–428.

Vanhonacker, F., Lengard, V., Hersleth, M., Verbeke, W. (2010). Profiling European traditional food consumers. *Brit. Food J.,* 112: 871–886.

Wallenbeck, A., Rydhmer, L., Thodberg, K. (2008). Maternal behaviour and performance in first-parity outdoor sows. *Livestock Science*, 116: 216–222.

Wallenbeck, A. (2009). Pigs for organic production. PhD-thesis. Acta Univ. Agric. Suec., 37: 1652–6880.

Wallenbeck, A., Keeling, L.J. (2013). Using data from electronic feeders on visit frequency and feed consumption to indicate tail biting outbreaks in commercial pig production. *J. of Anim. Sci.*, 91: 2879–2884.

Weissmann, F., Biedermann, G., Klitzing, A. (2005). *Performance, carcass and meat quality of different pig genotypes in an extensive outdoor fattening system on grass clover in organic farming*.

Wolfert, Sjaak, Ge, Lan, Verdouw, Cor, Bogaardt, Marc-Jeroen (2017). *Big Data in Smart farming – A review*.

https://www.sciencedirect.com/science/article/pii/S0308521X16303754.

Zerboni von H.N., Grauvogl, A. (1984). *Spezielle Ethologie Schwein. In: Bogner, H. and Grauvogl, A. (Hrsg.J: Verhalten landwirtschaftlichen Nutztiere*. Verlag Eugen Ulmer, Stuttgart, p. 246–297.

An Agent-Based model of grazing behaviour in dairy cows

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Abstract

Agent-Based Models (ABMs) are especially useful to represent complex systems, such as intake dynamics in grazing animals. The aim of this work was to develop an ABM to simulate the observed daily intake dynamic in grazing cows at the Universidad de Antioquia dairy farm in North-Antioquia, Colombia. Our ABM represents interactions between two agents: grass area and cows. In model developing, the grass dry matter (gDM) available (g of gDM/m^2) and its distribution in grass area, and the grass intake rate in housed cows were determined. In model verification, indirect observations (i.e. monitoring with electronic devices) of intake dynamic in 25 grazing Holstein cows were made. The grass availability observed, per square meter, at the Universidad de Antioquia dairy farm was classified into three groups: High, Medium and Low supply (338.5, 195.6 and 109.9 g of gDM/m^2, respectively). The Medium grass group had the highest prevalence (60%). The grass intake rate and the grass intake time observed in indoor cows was 26.8 ± 5.6 g of gDM/min and 469 ± 73 min/day, respectively. Indirect observation of cows' grazing behaviour at the Universidad de Antioquia dairy farm showed high grass intake after each milking, and very low grass intake overnight. Our ABM was coded and simulated in Unity3D development platform. Model verification showed that the intake dynamic in our ABM was very similar to the intake dynamic observed in real cows. The results indicate the enormous potential of ABM to simulate complex farm processes, especially in grass-based systems.

Keywords: Agent-based models, intake dynamic, grazing systems, Unity3D

Introduction

In grazing ruminants, intake is influenced by several factors including yield potential, live weight, age, reproductive stage, individual grazing behaviour, grass availability and quality, and prairie botanical composition (Decruyenaere *et al.*, 2009). Because of that, consistent and accurate intake predictions in grazing animals are difficult to achieve. However, moderately successful intake models could be a useful tool for decision-making in grass management and to improve livestock systems productivity. As proposed by Ruelle *et al.* (2015), to develop an intake model it is important to consider that grass intake is highly dependent on animal characteristics, grass availability and quality, and interactions between animals, and between animals and pasture during defoliation process.

Although there are several models to simulate grass intake, to include all grazing system components in these models is complex. For example, GrazeIn (Delagarde *et al.*, 2011) is a static herd grazing model where animal characteristics, grass supply, grazing duration, and grass height are taken into account. But as GrazeIn model's authors mentioned (Delagarde *et al.*, 2011), this model does not simulate grass height changes over time, which means that simulate forage supply impact on grazing activity is not represented. A similar limitation has been detected in the model developed by Baudracco *et al.* (2010), given that this model does not take into account grass height and defoliation (Ruelle *et al.*, 2015). DairyWise (Schils *et al.*, 2007) is a complete dairy farm model which describes

technical, environmental and financial processes. Although paddocks are independently represented in this model, the grazing process is not accurately simulated (Ruelle *et al.*, 2015).

Model limitations indicated above could be corrected by using Agents-Based Models (ABMs), where the most relevant grazing system components can be explicitly represented and where the system behaviour emerges as a consequence of components interactions. Jablonski *et al.* (2018) declared to be the first developers of an ABM to simulate grazing in cattle. These authors constructed a spatially explicit model of cattle behaviour in a meadow with *Delphinium geyeri*, a toxic plant. This model demonstrates the great potential of ABMs to simulate grazing dynamics, by including fundamental aspects of livestock performance into heterogeneity ecological. The aim of the present work was to develop an ABM to simulate Holstein cows' intake dynamic in a dairy farm from North-Antioquia, Colombia.

Materials and methods

Our ABM description follows the "Overview, Design Concepts and Details (ODD)" protocol (Grimm *et al.*, 2010).

Generalities

Purpose. Simulate the intake dynamic in Holstein cows from Universidad de Antioquia dairy farm. This farm is a grass-based dairy system located in a low mountain rain forest habitat in North-Antioquia, Colombia, with a height above sea level between 2,471–2,499 m, an average temperature of 16 °C and coordinates N 6°27'094, W 75°32'678.

Agents. Our ABM has two agents: Grass area and Cows. The grass area is a set of fixed agents with a constant area (1 m^2 per agent). These agents constitute a virtual grass field (2,500 m^2). Cows represent Holstein cows with 5.4 ± 1.4 years of age, 588.5 ± 88.1 kg of body weight, 3 ± 1 calving, 148 ± 141 days in milk, and 25.6 ± 9.0 liters of milk per day per cow.

Variables. Each square metre in the grass area has four variables: grass Dry Matter (gDM), damage score which represents the grass degradation due to cows contact and contamination, colour and height (cm). Each cow has variables related to its movement (i.e. individual speed, separation, alignment and cohesion inside the group), and dry matter intake (i.e. accumulative intake (gr), intake time (min) and grass intake rate (g of gDM/min)).

Scales. The model is temporal and spatially explicit, it simulates cows' intake dynamics during 24 hours in a grass area of 2,500 m^2. All state variables are updated in each simulation cycle. Each cycle is done in one real second which corresponds to one minute of simulation. It is possible to accelerate the simulation speed.

General process description. Cows' intake dynamic is simulated as follows: the milking routine starts at 05:00 h. Milking time (min/cow) and grain intake (g/cow) during milking are calculated using the individual milk yield. Animals can access the grazing area when all cows have been milked. Total grazing area is divided into two. The first-half area is available after morning milking, and the whole area is available after afternoon milking (14:00 h). During grazing, the animals are divided into subgroups to perform random grass searches, each subgroup prioritises sites with high grass supply and low grass damage to eat. The grazing probability depends on grass supply and time of day. Therefore, grazing activity increases after each milking. After 18:00 h, cows reduce their activity, and grazing probability is very low all night long.

Design concepts

Fundamental principles. Our ABM guiding principle is group grazing behaviour in dairy cows. The behavioural approach leads to a complex network of decisions, where animal responses to stimuli tend to be more multifaceted (McLane *et al.*, 2011). The coding process was carried out using concepts reported in literature and milking routines, and animal behaviours observed in the Universidad de Antioquia dairy farm. The cows' intake events coded were: group behaviour, milking schedules, interaction between animals, interaction between animals and grass area, nocturnal animal behaviour and grass defoliation, deterioration and contamination. During model development, it was checked graphically that virtual cows acted similarly to real cows, through a visual cleansing constant process (Augusiak *et al.,* 2014).

Adaptation and objectives. During simulation, each cow adapts its grass intake rate and grass search pattern according to grass offer and time of day. The random grass search is carried out in areas with greater and better forage offer. Therefore, cows' objective is to maximise grass intake, while following typical behaviour observed in gregarious animals.

Perception and interaction. Each cow perceives its neighbours to determine the distance and orientation of animals around them. This information is used to update its position in each simulation cycle. To find areas with greater and better forage offer, each animal subgroup has access to the DM and damage score in the grass square metres around them.

Stochasticity. Interactions between cows, and between cows and grass area are moderately stochastic, given that the grazing decision and the grass intake rate are defined using pseudo-random numbers generated by each cow in each simulation cycle. These numbers are generated within ranges reported in literature or observed at the Universidad de Antioquia dairy farm.

Details

Initialization. The simulation area is 2,500 m^2. To execute our ABM, users must define the grass distribution percentages in the prairie (% High, Medium and Low grass supply) and the mean forage supply in each grass level (g of gDM/m^2). Users must also enter cows' characteristics (i.e. the minimum and maximum milk yield and the number of cows). These values are used to generate and distribute square metres with high, medium or low grass supply into the grazing area, and to calculate grain intake and milking time per cow. Also, the minimum and maximum grass intake rate (g of gDM/min) must be entered by users. All square meters are initialised with zero damage score, and its height and colour depend on its grass offer.

Although each user can initialise our ABM according to their needs, some reference values are proposed for minimum and maximum grass intake rate (g of gDM/min). To obtain these reference values, the grass intake rate was determined as follows.

In the Universidad de Antioquia dairy farm, the grass intake rate (g of gDM/min) was determined in five cows, which were housed eight weeks in cubicles and fed *ad libitum* with fresh Kikuyo grass (*Pennisetum clandestinum*) and grain, according to individual requirements. The grass was offered twice a day, at 07:00 and 15:00 h. The grain was offered during milking (06:00 and 14:00 h). The grass intake rate was calculated, during two consecutive days, by simply dividing the daily grass intake by the daily grass intake time. To do this, the daily grass intake (g of gDM/day) was measured taking into account the grass offered and rejected. The daily grass intake time (min/day) was recorded using the accelerometer methodology proposed by Andriamandroso *et al.* (2017). For this, each cow was equipped with a mobile phone attached to the back of its head. In each device,

an Android application was installed to record the values of X, Y and Z axes from the accelerometer contained in each unit. This methodology is based on the assumption that animal's head position is an intake indicator and that this position can be clearly determined using acceleration changes recorded by an accelerometer placed on the animals' head or neck. As indicated by Andriamandroso *et al.* (2017), previous observations were made to identify which acceleration values indicate that the cow bowed its head to eat. The acceleration value changes were analysed in Excel software to determine the daily intake time in each animal (min/day).

Sub-Models:

Milking time: Each cow's milking time is calculated according to the milking routine observed at the Universidad de Antioquia dairy farm. The milking speed is determined individually as minutes per litre of milk per cow.

Grain intake: The amount of grain eaten by each cow is calculated following the observed management at the Universidad de Antioquia dairy farm. In this farm, the cows eat one kilogram of grain for every four litres of milk produced. The milk yield of each cow is randomly generated between the minimum and maximum milk yield proposed by the model's users.

Herd movement: The way in which the animals move on the grass area was simulated following the concepts proposed by Reynolds (1987) and the libraries developed by Srinavin Nair (2015). Reynolds (1987) developed a computerised model of coordinated animal movement, similar to a flock of birds or shoals of fish. This model basically consists of three very simple behaviours that describe how an individual manoeuvres depending on the positions and speeds of his closest neighbors, as well: a) Separation: move to avoid crowding of individuals at one point in the group, b) Alignment: turn to the average direction of nearby neighbours and c) Cohesion: locate in the average position of nearby neighbours.

Grass search. During simulation, each subgroup of animals searches a grass area with a high grass supply. Every time that the subgroup of animals finds a better area to graze, all animals into the group moves towards this new area to perform random grass search and to start defoliation.

Defoliation. The grass intake rate (g of gDM/min) is not constant. This rate depends on grass supply (g of gDM/m^2) in the square metre selected by each cow to graze. The grass intake rate is an interpolation between the minimum and maximum grass intake rates proposed by the model's user.

Model verification. To verify that intake dynamic simulated by our ABM corresponds to real grazing cows' behaviour, indirect observations of grazing cows were made at the Universidad de Antioquia dairy farm. The daily grazing dynamic of 24 cows was determined using the accelerometer methodology proposed by Andriamandroso *et al.* (2017), described previously.

Results and discussion

Milking time and grain intake. Observations made at the Universidad de Antioquia dairy farm allowed to determine that milking time per cow is 0.89 ± 0.2 minutes by litre of milk produced. The 61.5 ± 3.7% of daily milk yield per cow is obtained in the morning milking. The ratio between milk yield and grain intake (L/kg) is four.

Table 1. Grass dry matter intake in indoor cows

Variable	N	Median	Standard deviation	Min	Max
Intake time (min/day)	10	383.1	74.8	300	501
Grass dry matter intake (kg of gDM/day)	10	9.9	1.3	7.5	11.4
Grass intake rate (g of gDM/min)	10	26.8	5.6	20	36.2

Grass intake rate in indoor cows. Table 1 shows median, minimum and maximum grass intake rate and grass intake time observed in indoor cows at the Universidad de Antioquia dairy farm. The grass intake rate and the grass intake time observed in indoor cows was 26.8 ± 5.6 g of gDM/min and 469 ± 73 min/day, respectively.

Model verification. Figure 1 presents a graphical comparison of the mean intake dynamic recorded using accelerometers in grazing cows, and the mean intake dynamic simulated by our ABM. It is observed that our ABM describes appropriately the cows' intake behaviour observed in grazing cows, where cows have a high grass intake after each milking and very low grass intake during the night.

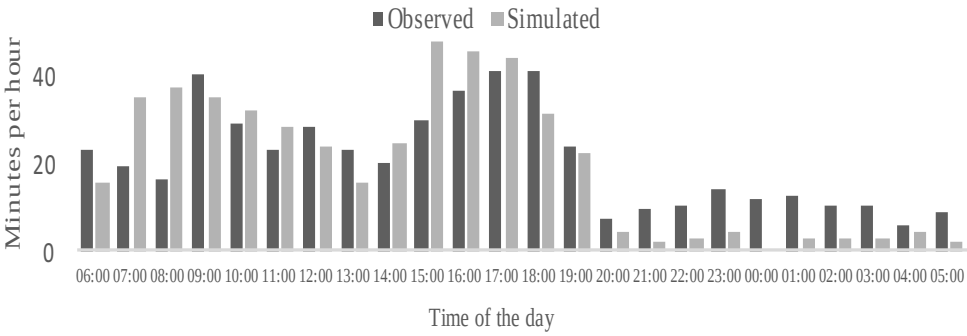

Figure 1. Intake dynamic (min/h) observed in grazing cows and simulated

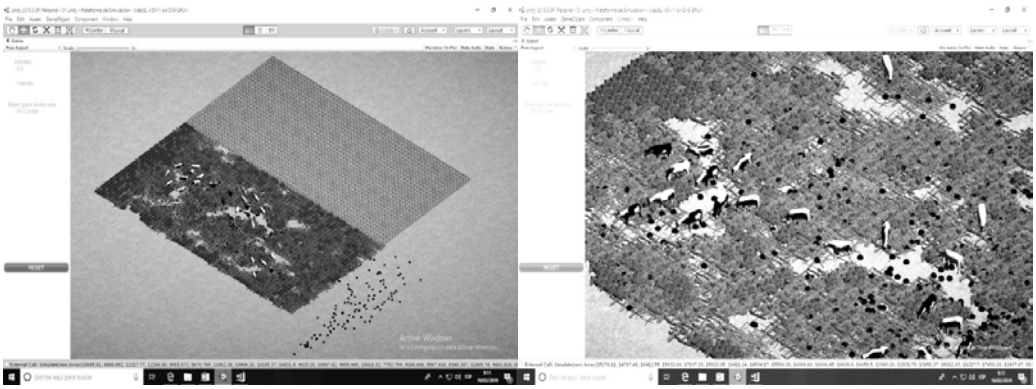

Figure 2. Model graphical user interface

The ABM developed in this work includes the effect of grass supply on grass intake rate and grass rejection that animals can have when grass is contaminated with faeces or trampled.

In addition, our ABM mimics the effect of time of day on grass intake dynamic observed in grazing cows. The analysis of grazing dynamic at the Universidad de Antioquia dairy farm demonstrated that there is a clear relationship between sunset time and grazing cessation in grazing cows, with a very few cows grazing at night. In addition, as observed by some authors (DeVries *et al.*, 2003), our ABM simulates two large grazing peaks which occur immediately after milking (Figure 1). During model development, it was considered as fundamental that Colombian dairy cows are grazing animals, which have a clearly defined intake pattern.

The grass intake time observed in grazing cows at the Universidad de Antioquia dairy farm (469 min/day) and the simulated grazing time in our ABM (463 min/day) are similar to those reported by Pérez-Prieto & Delagarde (481 min/day, 2012). Some authors (Gregorini, 2012) explain the intake dynamic based in diurnal fluctuations in intensity of light which stimulates a circadian release of neuropeptides and hormones, providing a signal to start or stop grazing. The grass intake estimated by our ABM (15.6 ± 2.3 kg gDM/day) is similar to those observed by other authors in Colombia. Diaz *et al.* (2017) found that grass intake in dairy cows was 13 ± 2.9 kg/cow/day. Several authors (Mojica *et al.,* 2009; Marín, 2013; Rojo, 2015) report similar values of grass intake in Colombian dairy cows.

Regarding grass intake rate, in a meta-analysis that included 66 articles, Pérez-Prieto & Delagarde (2012) found a minimum and maximum grass intake rate of 16.2 and 44.8 g of gDM/min in dairy cows, respectively; with average values between 26.3–29.7 g of gDM/min. Ruiz-Albarrán *et al.* (2012) found an average grass intake rate between 20.6–30.5 g of gDM/min; which is a value range similar to observed values in indoor cows at the Universidad de Antioquia dairy farm (26.8 ± 5.6 g of gDM/min). These results could indicate that grass intake rate is not substantially affected by grass supply; since the amount of grass ingested in each bite apparently is very similar when cows consume cut grass, and when cows must cut the grass by itself during grazing.

Conclusions

This paper proposed an Agent-Based Model to simulate intake dynamic in grazing cows. The results indicate the enormous potential of this model to simulate complex farm processes, especially in grass-based systems.

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References

Andriamandroso, A.L.H., Lebeau, F., Beckers, Y., Froidmont, E., Dufrasne, I., Heinesch, B., ... y Bindelle, J. (2017). Development of an open-source algorithm based on inertial measurement units (IMU) of a smartphone to detect cattle grass intake and ruminating behaviors. *Computers and Electronics in Agriculture*, 139: 126–137.

Augusiak, J., Van den Brink, P.J., y Grimm, V. (2014). Merging validation and evaluation of ecological models to 'evaludation': a review of terminology and a practical approach. *Ecological Modelling*, 280: 117–128.

Baudracco, J., Lopez-Villalobos, N., Holmes, C.W., y Macdonald, K.A. (2010). Prediction of herbage dry matter intake for dairy cows grazing ryegrass-based pastures. *In Proceedings of the New Zealand Society of Animal Production,* 70: 80–85. New Zealand Society of Animal Production.

Decruyenaere, V., Buldgen, A., y Stilmant, D. (2009). Factors affecting intake by grazing ruminants and related quantification methods: a review. *Biotechnologie, Agronomie, Société et Environnement*, 13(4): 559–573.

Delagarde, R., Faverdin, P., Baratte, C., y Peyraud, J.L. (2011). GrazeIn: a model of herbage intake and milk production for grazing dairy cows. 2. Prediction of intake under rotational and continuously stocked grazing management. *Grass and Forage Science*, 66(1): 45–60.

DeVries, T.J., Von Keyserlingk, M.A.G., Weary, D.M., y Beauchemin, K.A. (2003). Measuring the feeding behavior of lactating dairy cows in early to peak lactation. *Journal of Dairy Science*, 86(10): 3354–3361.

Díaz, E.M., Ledesma, L.M., y Arizala, J.A. (2017). Consumo de materia seca en un sistema silvopastoril de Tithonia diversifolia en trópico alto. *Agronomía Mesoamericana*, 28(2): 389–403.

Gregorini, P. (2012). Diurnal grazing pattern: its physiological basis and strategic management. *Animal Production Science*, 52(7): 416–430.

Grimm, V., Berger, U., DeAngelis, D.L., Polhill, J.G., Giske, J., y Railsback, S.F. (2010). The ODD protocol: a review and first update. Ecological modelling, 221(23): 2760–2768.

Jablonski, K.E., Boone, R.B., y Meiman, P.J. (2018). An agent-based model of cattle grazing toxic Geyer's larkspur. *PloS one*, 13(3): e0194450.

Marín, A. (2013). Estimación del inventario de emisiones de metano entérico de ganado lechero en el departamento de Antioquia, Colombia (Doctoral dissertation, Tesis MSc., Universidad Nacional de Colombia, Medellín, COL).

McLane, A.J., Semeniuk, C., McDermid, G.J., y Marceau, D.J. (2011). The role of agent-based models in wildlife ecology and management. *Ecological Modelling*, 222(8): 1544–1556.

Mojica, J.E., Castro, E., León, J., Cárdenas, E.A., Pabón, M.L., y Carulla, J.E. (2009). Efecto de la oferta de pasto kikuyo (Pennisetum clandestinum) sobre la producción y calidad composicional de la leche bovina. *Livestock Research for Rural Development*, 21(1): 1–12.

Pérez-Prieto, L.A., y Delagarde, R. (2012). Meta-analysis of the effect of pregrazing pasture mass on pasture intake, milk production, and grazing behavior of dairy cows strip-grazing temperate grasslands. *Journal of Dairy Science*, 95(9): 5317–5330.

Reynolds, C.W. (1987). Flocks, herds and schools: A distributed behavioral model. In *ACM SIGGRAPH computer graphics*, 21(4): 25–34. ACM.

Rojo Bedoya, J.M. (2015). Efecto de la suplementación con aceite de semilla de girasol y aceite de pescado sobre la producción y composición de la leche en vacas holstein. (Master dissertation, Tesis MSc., Universidad de Antioquia, Medellín, COL).

Ruelle, E., Shalloo, L., Wallace, M., y Delaby, L. (2015). Development and evaluation of the pasture-based herd dynamic milk (PBHDM) model for dairy systems. *European Journal of Agronomy*, 71: 106–114.

Ruiz-Albarrán, M., Balocchi, O.A., Noro, M., Wittwer, F., y Pulido, R.G. (2012). Effect of increasing pasture allowance and grass silage on animal performance, grazing behaviour and rumen fermentation parameters of dairy cows in early lactation during autumn. *Livestock Science*, 150(1): 407–413.

Schils, R.L.M., De Haan, M.H.A., Hemmer, J.G.A., Van den Pol-van Dasselaar, A., De Boer, J.A., Evers, A.G., ... & Zom, R.L.G. (2007). DairyWise, a whole-farm dairy model. *Journal of Dairy Science*, 90(11): 5334–5346.

Srinavin Nair (2015). *Zen Coder Games*. https://github.com/ZenCoderGames/ZAI.

Development of automata to improve individual management of health in pig production

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Abstract

As post-weaning piglets have a weak immune system, this study is focused on weaned piglets. The main goal is to develop automata to collect several individual data on the behaviour and technical performances of piglets. We set up on IFIP's (French pig and pork institute) experimental farm in Romillé (France), six pens of 17 piglets with three types of automata: a connected feeder, a connected drinker and an automatic weighing station located in front of the drinker. Each automat uses radiofrequency identification to detect the individual ear tag of the piglets. For the weighing station, we compared the average of the individual data from the automatic device to manual individual weighing to assess the accuracy. The average difference was less than 1.5% and non-significant when compared within a given weight range (light/medium/heavy). Previous studies illustrate the importance of weight in correctly understanding piglets' feeding and drinking behaviour. On average, individual water consumption was 10.5% (± 5.2) and for feed was 4.6% (± 1.7) of body weight. For both feeding and drinking there was a large inter and intra individual variability: approximately 30-40% for water and 20-30% for feed. After development, optimisation and tests of these automata, all the data were collected in one database. Further research, in progress, is needed to utilise these data collection techniques in the development of an individual early diseases detection for piglets.

Keywords: weaned piglet, individual data, drinking behaviour, feeding behaviour, weighing station

Introduction

In pig production, as in poultry, rabbit, or calf production, antibiotic treatments are mainly administered orally. Treatments via the food, largely predominant a few years ago, are decreasing in pig farms (66.9% of treatments in 1999, 47.2% in 2009 and 35.8% in 2013), while treatments via drinking water are increasing: 21.9% of treatments in powder form and oral solutions in 1999, 40.3% in 2009 and 51% in 2013 (ANMV, 2014). In this context, respect of the dosage for treatments depends on the quantity of water and feed consumed by animals. In general, calculation of antibiotics doses given to a piglet is based on defined constants for a healthy animal: feed consumption around 4 – 5% of body weight/day and water consumption close to 10% of body weight /day. However, many parameters can modify these levels of consumption and therefore create variation in antibiotic dosage to be sure that each animal has good treatment: level of social competition, type of drinker or trough (Li *et al.*, 2005; Turner *et al.*, 1999), emergence of pathologies like hyperthermia, dehydration, apathy (Pijpers *et al.*, 1991), inter and intra variability of each animal (healthy or not). In the literature, most of the studies work on it but for a group of animals (Brumm *et al.*, 2000; Kashihaa *et al.*, 2013; Villagra *et al.*, 2007). One way to answer this issue is to work on the individual scale.

To achieve it, the first goal of this study is to develop and validate automata to collect daily and individual body weight, drinking and feeding behaviour of piglets. As post-weaning piglets are sanitary weak, this study is focused on weaned piglets.

This type of automata can offer huge opportunity to manage animals' health status.

Several authors showed the link between automatic detection changes of water uses and welfare monitoring tools (Madsen and Kristensen, 2005; Madsen *et al.*, 2005) or emergence of pathologies (Brumm, 2006) at a batch level. Ahmed *et al.* (2015) also showed the relation between feed intake, water consumption and occurrence of stress or disease.

The second goal of this study is to build and normalise a database, in which it is possible to work on the link between the individual health status of animals and data extract from these automata.

Material and methods

Periods of trails

Trials were conducted on the experimental station of Ifip in Romillé (Brittany, France) with two steps:

- *Validation period:* between 2016 and 2018, eight trials were implemented to develop automata: connected drinker, connected feeder and automatic weighing station. The first ones were used to fix electronic and mechanical issues on devices. The last ones were used to validate the good working condition of automata to be sure that they didn't affect piglets' performances (animals on automata VERSUS animals on traditional equipment) and to measure accuracy of the data collected.
- *Operational period:* two trails were implemented from 28 July to 21 August 2018 (the last four weeks of the post-weaning period) and from 13 September to 23 October 2018 (on the entire post-weaning period).

The article is particularly focused on the operational period.

Automata to collect individual data on piglets

Automata have been developed with a French firm specialising in animal livestock housing (Asserva). The main goals were to isolate and identify pigs in front of each device, then to record their individual data on a computer. They used RFID (Radio Frequency IDentification) antenna to detect the electronic and individual ear tag of each pig. Each automat had a width calculated to have only one piglet inside at the same time.

- Automatic weighing station: It is connected to the drinkers in a single stall made from a stainless steel box hanging from two force sensors (precision ± 10 g). A side partition protects the weighing system and prevents disturbance by other animals. The connected drinker and the weighing system use the same radiofrequency identification antenna located behind the drinking bowl to check the ear tag of the animal in the stall. Every time the RFID antenna detects a piglet, a weight is recorded.
- Connected drinker, Aqualab, is composed of an antiwastage bowl drinker surrounded by shoulder partitions, a precision water meter (± 0.01 l for piglets). This automat can record water quantity used and the duration of each visit. The amount of water recorded includes real consumption of pig and water wastage. This last is considered to be like a part of the natural drinking behaviour of a pig.
- Connected feeder, PigInsight, is composed of a conical trough with a specific sensor at the bottom to detect dry feed, shoulder partitions and a motor equipped with a feeding screw overcome by a feed hopper. The sensor inside the trough pilots the feeding distribution. When a piglet is detected by the RFID antenna, either the sensor detects feed in the trough thus the piglet should consume it before the next distribution or there is nothing in the trough and a feed dose of 10 g (± 2 g) is delivered.

Figure 1. Connected drinker with an automatic weighing station, a pen of weaned piglets with automata, entrance of the connected feeder (from the left to the right)

Housing conditions

After weaning, 102 piglets, 28 days old, were allocated in six pens of 17 animals. Three weight groups were created with two pens each (heavy, medium and light with respectively a mean weight around 11.1 kg, 9.1 kg and 7.0 kg). Each pen had one connected drinker (Aqualab) with an automatic weighing station and two connected feeder (PigInsight).

The water flow was adjusted to one litre/minute and it was checked every 14 days and adjusted if necessary. The daily water consumption of the six pens was also recorded manually. Piglets were individually weighed every seven days with a mobile weighing station located in the room's corridor to check accuracy of the automatic system. Once a week, one feeding dose of 10 g (± 2 g) was collected to each connected feeder and weighed on a precision scale. This operation was repeated five times per automate. If there was too much difference between the real weight and the theoretical dose of 10 g, the operator modified the feeding screw speed.

Pens were warmed at 28 °C at the beginning of post-weaning and temperature dropped progressively to obtain 24 °C at the end of the trial. The housing conditions were identical for these trails.

Animal's health status

Each day, animals were observed by the station's staff to assess their health status. There was a specific focus on the most frequently observed diseases in pig barns: digestive (especially diarrhoea), locomotive (especially gait and lameness) and respiratory (especially number of cough) disorders. In addition, individual observations on the general health status of piglets were done by an external operator twice a week. For each disorder, a note is given related to the severity: 0 is linked to a healthy piglet, 1) the animal begins to be sick (digestive: soft faeces; locomotive: change of gait; respiratory: less than three coughs during 20 min), 2) the animal is clearly sick (digestive: liquid faeces; locomotive: leg not resting on the ground; respiratory: more than three coughs during 20 min). This evaluation was based on a rating grid inspired by the Welfare Quality approach. In addition, all remarks relating to veterinary interventions were recorded.

Selection of healthy animals and creation of the data base

Thanks to individual observations of piglets, a daily sanitary score was calculated for each piglet: it is the addition of three notes (one for each type of disorder: digestive, locomotor and respiratory). For each period studied, individual daily scores were added per piglet which is called the health indicator. If the health indicator was below or equal to one, the piglet is considered as a healthy animal, otherwise, the animal is considered sick.

On the post-weaning period of five weeks, three phases were analysed separately: Phase 1, the two first weeks after weaning; Phase 2, the three last weeks of the post-weaning period; Phase 1 + 2, the entire period of post-weaning.

On each phase, a health indicator was calculated for each piglet and only healthy animals were kept for analyses.

Statistical analyses

The data analysis by descriptive statistics was carried out under R version 3.3.1. The comparison of water and feed consumption between pens according to their equipment (traditional drinker or trough VS connected system) was carried out using a non-parametric test (Kruskal-Wallis). The accuracy of the automatic weighing station was done with Wilcoxon test.

Results and discussion

Data extracted from automatic weighing station

During the validation period, between 2016 and 2018, a specific trial has been done to test the accuracy of the automatic weighing station. Fifty one piglets were weighed with mobile weighing station, considered as a reference, and these weights were compared to 34 173 weights (51 piglets * 35 days of trial * about 20 visits per day and per piglet on the automatic weighing station) obtained thanks to weighing stations in front of each connected drinker. The gap between automat and control weights was on average 1.5% (Table 1). At 56 days of age, the gap was close to 3% and approached the significance threshold. However, on average, the daily weighing data is an average of about fifteen values taken at different times of the day. Therefore, this value was considered as precise and exploitable. In this study, daily weights were used to express the water and feed consumption of piglets per kilogram of body weight.

Table 1. Weight of piglets (kg) with the automatic weighing station and with manual weighing station (reference)

Age of piglets	Automat	Control	p-value
35 days	13.1 (± 1.8)	13.0 (± 1.9)	0.84
42 days	17.0 (± 2.8)	16.7 (± 3.1)	0.09
49 days	22.3 (± 2.7)	22.2 (± 3.0)	0.29
56 days	26.8 (± 2.4)	27.6 (± 3.3)	0.06

Data extracted from connected drinker

Between 2016 and 2018, the validation period, several trails compared water consumption of piglets according to their drinker: a traditional bowl drinker, a connected drinker with shoulder partitions and a connected drinker with an automatic weighing station. In pen of 17 piglets, the average water consumption did not differ significantly according to drinking equipment. Therefore, shoulder partitions or weighing station did not seem to interfere with piglets' access to drinker.

On operational trials, in July and September, results were close to the study of Rousselière *et al.* in 2017. On the entire period of post-weaning, water consumption of piglets was close to 10 % of body weight (10.5 in this study) but in fact, it was not constant. As shows in Table 2, at the beginning of the post-weaning period, Phase 1, it was close to 8% of

body weight and it increased to 11 % of body weight during the Phase 2. The number of visits to the drinker was constant during the trial and between 25–30. However, the water consumption per visit increased. During the Phase 1, 56.4 ml per visit was recorded; however during Phase 2, 115 ml was recorded. This difference is most likely due to two factors: 1) the piglets were larger during Phase 2; 2) Phase 1 piglets were most likely in a distressful situation (anorexia, thermal comfort, feeding transition…) and discovery of a new environment after weaning.

Table 2. Drinking behaviour of piglets during the post-weaning period

Parameters **N = Number of piglets with a heathy indicator ≤ 1** **Nb D = Number of days**		**July 2018** **Phase 2** **N = 69** **Nb D =22**	**Sept 2018** **Phase 1** **N = 85** **Nb D =13**	**Sept 2018** **Phase 2** **N = 71** **Nb D =24**	**Sept 2018** **Phase 1+2** **N = 61** **Nb D =37**
Daily consumption	Average l/kg of body weight (BW)	0.111	0.080	0.113	0.105
	Standard deviation	0.061	0.053	0.046	0.052
Number of visits (with or without consumption)	Average	30	24	27	25
	Standard deviation	8	7	8	6
Water consumed per visit	Average (ml)	110.0	56.4	122.8	106.8
	Standard deviation	114.8	57.8	118.6	110.5

Table 3 shows great inter-individual variability since the coefficient of variation (CV) calculated from the average of the individual average values obtained per piglet was 36.9% on the entire period of post-weaning. It was even higher during the Phase 1 with 42.0% before to decreased in Phase 2 with 26 -28 %. On intra-individual scale, the daily consumption expressed per kilogram of BW was also very variable, the coefficient of variation of the individual measurements being on average 38.5% (± 11.7). Again, this variability was higher during Phase 1 than Phase 2 with respectively an average CV of 45.8–27-28%.

Data extracted from connected feeder

Between 2016 and 2018, the validation period, several trails compared feed consumption of piglets according to their trough: a traditional collective trough and an individual connected feeder. In pen of 17 piglets, the average feed consumption did not differ significantly according to feeding equipment if there were two connected feeders per pen. With only one connected feeder per pen, piglets with a connected feeder had significantly poorer growth performance.

Table 3. Variability of drinking behaviour of weaned piglets

Scale	Parameters N = Number of piglets with a heathy indicator ≤ 1 Nb D = Number of days	July 2018 Phase 2 N = 69 Nb D =22	Sept 2018 Phase 1 N = 85 Nb D =13	Sept 2018 Phase 2 N = 71| Nb D =24	Sept 2018 Phase 1+2 N = 61 Nb D =37
Inter - individual	Average[1] l/kg of body weight (BW)	0.111	0.080	0.113	0.105
	Standard deviation[2]	0.031	0.034	0.030	0.039
	Coefficient of variation[3] (CV) %	28.1	42.0	26.8	36.9
Intra - individual	Average CV[4] %	28.3	45.8	27.4	38.5
	Standard deviation of CV[5]	9.1	17.7	9.5	11.7

1= Average of the individual averages of each piglet; 2 = Average of the individual standard deviation of each piglet; 3 = 2/1 each piglets; 4 = Average of individuals CV of each piglet; 5 = Standard deviation of individual CV of each piglet

Table 4. Feeding behavior of piglets during the post-weaning period

Parameters N = Number of piglets with a heathy indicator ≤ 1 Nb D = Number of days		July 2018 Phase 2 N = 69 Nb D =22	Sept 2018 Phase 1 N = 85 Nb D =13	Sept 2018 Phase 2 N = 71| Nb D =24	Sept 2018 Phase 1+2 N = 61 Nb D =37
Daily consumption	Average kg/kg of body weight (BW)	0.051	0.038	0.051	0.046
	Standard deviation	0.012	0.020	0.014	0.017
Number of visits (with or without consumption)	Average	47	24	48	41
	Standard deviation	17	8	16	13
Feed consumed per visit	Average (g)	23.3	16.3	21.9	20.3
	Standard deviation	26.7	13.6	25.0	22.2

Over the entire post-weaning period, piglets feed consumption was 4.6% of body weight. As shown in Table 4, the beginning of the post-weaning period, Phase 1, the feed consumption was slightly lower, 3.8% of body weight, than during Phase 2, 5.1% of body weight. The number of visits and the feed consumption per visit increased with the age of the animal changed as the piglets grew (Phase 1, piglets ate an average of 13.6 g per visit and had 24 feeder visits;

Phase 2, piglets ate an average of 25-26 g per visit and had 47-48 feeder visits per day).

Table 5 shows great inter-individual variability since the coefficient of variation (CV) calculated from the average of the individual average values obtained per piglet was 29.9% on the entire period of post-weaning. It was even higher during the Phase 1 with 38.5% before to decreased in Phase 2 with 18-20%. On intra-individual scale, the daily consumption expressed per kilogram of BW followed exactly the same trend, the coefficient of variation of the individual measurements being on average 30.6% (± 9.5) and it was higher during Phase 1 than Phase 2 with respectively an average CV of 40.7% and 18-20%.

Table 5. Variability of feeding behavior of weaned piglets

Scale	Parameters N = Number of piglets with a heathy indicator ≤ 1 Nb D = Number of days	July 2018 Phase 2 N = 69 Nb D =22	Sept 2018 Phase 1 N = 85 Nb D =13	Sept 2018 Phase 2 N = 71 Nb D =24	Sept 2018 Phase 1+2 N = 61 Nb D =37
Inter – individual	Average[1] kg/kg of body weight (BW)	0.051	0.038	0.051	0.046
	Standard deviation[2]	0.010	0.014	0.009	0.014
	Coefficient of variation (CV)[3] %	20.0	38.5	18.2	29.9
Intra - individual	Average CV[4] %	20.1	40.7	18.3	30.6
	Standard deviation of CV[5]	3.7	14.6	7.1	9.5

1 = Average of the individual averages of each piglet; 2 = Average of the individual standard deviation of each piglet; 3= 2/1 each piglets; 4 = Average of individuals CV of each piglet; 5 = Standard deviation of individual CV of

Conclusions

After several months of development, the connected drinker equipped of a weighing station and the connected feeder offer huge opportunities to obtain individual data on the natural behaviour of weaned piglets. On average, results are really close to the bibliography with 4-5% and 10% of the body weight for the consumption of feed and water. However, it hides an important variability both to inter and intra individual scale and according to piglets' age (Phase 1, Phase 2 or the entire period of post-weaning). Even on healthy animals, this variability on feed and water consumption is regularly close to 30-35 %. It will be probably more important on sick animals which can modify their natural behaviour. The next step is to check whether early detection of diseases is possible by individual monitoring of weight gain, water and feed consumption of animals. At this moment, trials are in progress on the experimental farm of Romillé, to develop tools on this concept by using artificial intelligence like machine learning. Several benefits are expected : i) rapid management of sick animals would prevent spread of disease and reduce total number of treated animals; ii) with more reactive treatment, pathologies or infections could also be more easily eliminated, with smaller amounts of antibiotics; iii) a lower severity of health disorders increases welfare and performances of animals.

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References

Ahmed, S.T., Mun, H.S., Yoe, H. and Yang, C.J. (2015). Monitoring of behavior using a video-recording system for recognition of *Salmonella* infection in experimentally infected growing pigs. *Animal,* 9: 115–121.

ANMV (2014). Suivi des ventes de médicaments vétérinaires contenant des antibiotiques en France en 2013. 73 pp.

Brumm, M.C., Dahlquist, J.M. and Heemstra, J.M. (2000). Impact of feeders and drinker devices on pig performance, water use, and manure volume. *Swine Health Production*, 8(2): 51–57.

Brumm, M. (2006). Patterns of drinking water use in pork production facilities. Nebraska Swine Reports. Paper 221.

Kashihaa, M., Bahra, C., Haredashta, S.A., Ottb, S., Moonsb, C., Niewoldc, T., Odbergb, F. and Berckmans, D. (2013). The automatic monitoring of pigs water use by cameras. *Computers and Electronics in Agriculture,* 90: 164–169.

Li, Y.Z., Chénard, L., Lemay, S.P., and Gonyou, H.W. (2005). Water intake and wastage at nipple drinkers by growing-finishing pigs. *Journal of Animal Science,* 83: 1413–1422.

Madsen, T.N., Andersen, S. and Kristensen, A.R. (2005). Modelling the drinking patterns of young pigs using a state space model. *Computers and Electronics in Agriculture*, 48: 39–62.

Madsen, T.N. and Kristensen, A.R. (2005). A model for monitoring the condition of young pigs by their drinking behaviour. *Computers and Electronics in Agriculture*, 48: 138–154.

Pijpers, A., Schoevers, E.J., Van Gogh, H., Van Leengoed, L.A., Visser, I.J., Van Miertet, A.S. and Verheijden, J.H. (1991). The influence of disease on feed and water consumption and on pharmacokinetics of orally administered oxytetracycline in pigs. *Journal of Animal Science,* 69: 2947–2954.

Rousselière, Y., Hémonic, A. and Marcon, M. (2017). Monitoring of the individual drinking behavior of healthy weaned piglets and pregnant sows. The 8th European Conference on Precision Livestock Farming, Nantes, France, 8 pp.

Turner, S.P., Adwards, S.A. and Bland, V.C. (1999). The influence of drinker allocation and group size on the drinking behaviour, welfare and production of growing pigs. *Animal Science,* 68: 617–624.

Villagra, A., Althaus, R.L., Lainez, M., Martinez, A.B. and Torres, A.G. (2007). Modelling of daily rhythms of behavioural patterns in growing pigs on two commercial farms. *Biological Rhythm Research,* 38: 347–354.

Recording the behaviour of grazing dairy cows to develop a sensor based health monitoring system

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Abstract

As dairy herd sizes continue to increase, the demand for digital solutions for monitoring the cows' health and welfare grows. Health disorders result in a change of behaviour which can be detected automatically by various systems for health monitoring in dairy cows available on the global market. For animals kept indoors, those systems reach high levels of accuracy and precision in detecting health disorders. On the contrary, for grazing situations the systems' performance is poor. In order to develop a system that detects the behaviour of grazing dairy cows and thereby identifies health disorders reliably, a large amount of behavioural data is needed and further factors influencing the behaviour of cows on pasture (e.g. temperature, precipitation, wind speed, available biomass, etc.) have to be measured. Therefore, grazing dairy cows were equipped with a sensor system attached to a collar, containing a three-dimensional accelerometer. The accelerometer recognised the cow's head and neck movements which are typical for each behavior (e.g. lying, grazing, ruminating). To assign the actual behaviour to the sensor data, the animals were recorded with cameras at the same time. Furthermore, climate data as well as bio and performance data of the animals were collected to allow the generation of algorithms for an automated recognition of animal behaviour. First results showed that the chosen methods provide a sufficient amount of data for the successful development of algorithms. After the algorithms are finalised, an evaluation of the system's accuracy and precision can be conducted.

Keywords: health monitoring, behaviour monitoring, dairy cows, pasture grazing

Introduction

In 2008, a German dairy farm had 42 milking cows on average, while in 2018 the average number of animals per farm was 65 (Statistisches Bundesamt, 2019). A similar development can be observed for dairy farms in Europe (Augère-Granier, 2018). With larger herd sizes, the demand for digital solutions for enhanced monitoring of the animals' health and welfare increases (Tullo *et al.*, 2016). Health disorders affect the behaviour of animals. By monitoring the behaviour continuously, the daily time spent on each behavioral pattern (e.g. grazing, lying, and ruminating) can be observed and changes can be detected. Changes in behaviour caused by health disorders often occur a few days before clinical symptoms appear (Stangaferro *et al.*, 2016a, 2016b, 2016c). The continuous monitoring of the animals' behaviour cannot be realised by manpower, therefore digital solutions, such as monitoring systems containing different sensors (e.g. accelerometer, magnetometer) are needed (Tullo *et al.*, 2016). Because of the earlier detection of health disorders by monitoring systems, the animal's health can be restored more quickly. Expenses for medication and veterinary treatment and the financial loss, e.g. caused by milk yield reduction can be minimized. In addition, the pain related to health disorders can be reduced or avoided, which increases animal welfare. Various systems for an automatised monitoring of animal behaviour are available on the global market. For their application on animals kept indoors, high levels of accuracy and precision in detecting changes in behaviour caused by health disorders have

been reported (Reiter *et al.*, 2018; Rutten *et al.*, 2013). For grazing situations, the systems' performance in detecting the correlating behavior is poor (Elischer *et al.*, 2013). The aim of the project is to develop a monitoring system that detects the animals' behaviour, its changes and thereby health disorders reliably in cows kept indoors in winter and on pasture in summer. To develop such a system, a large amount of behavioural data for the development of appropriate algorithms is needed, especially for grazing as the main behaviour on pasture. In addition, the factors which influence the animals' behaviour on pasture (e.g. temperature, humidity, precipitation, wind speed, available biomass, etc.) are more extreme and variable than in a barn and have to be measured simultaneously to the behaviour monitoring in order to select relevant variables for developing sufficiently reliable algorithms.

Material and methods

In order to collect the required behavioural data, two sets of behaviour observations were conducted in the late grazing period 2018 (September and October). The observation took place on a farm in Upper Bavaria, Germany, with 44 Simmental dairy cows kept on pasture with free access to a loose barn. The cows were milked twice daily in a herringbone milking parlor. Six clinically healthy cows were selected, dependent on lactation number (median lactation number: 3; minimum: 2; maximum: 4) and equipped with the prototype of a monitoring system developed by Blaupunkt Telematics GmbH. The monitoring system contained a three-dimensional accelerometer recognising the cows' head and neck movements with a frequency of 10 Hz. At the same time, the animals were recorded with cameras (GoPro Hero5) for six hours per day from 10 am to 4 pm. Besides those datasets consisting of sensor data generated by the monitoring system and the video recordings, different factors that possibly influenced the animal behaviour were recorded. A weather station measured air temperature, humidity, precipitation, wind speed and global radiation with 0.1 Hz throughout the observation period at a representative point on the pasture. Furthermore, information concerning the animals' bio and performance data was recorded (Table 1).

Table 1. Bio and performance data of the observed cows

Cow	Age (a)	Number of lactation (n)	Last calving (dd/mm/yy)	Calving interval (d)	Average milk yield ($kg*a^{-1}$)
1	6	4	25/01/18	332	7,132
2	5	3	26/02/18	328	5,230
3	5	3	17/12/17	329	5,347
4	5	3	22/01/18	353	6,338
5	4	2	29/01/18	352	6,811
6	5	3	11/12/17	319	4,882

After the observations, video data were analysed. Based on an ethogram (Table 2), the behaviour of each observed animal was determined at every point of time. Those datasets are the base for the development of algorithms for an automatic detection of the animals' behaviour in the ongoing project. In addition, behavioural data from videos allowed a first analysis of the cow's behaviour.

Table 2. Ethogram of a cow kept on pasture

Item	Definition
Main activity	
Grazing	The cow bites off, chews and swallows the grass and moves forward with bowed head.
Walking	The cow is moving forward with head raised higher than the carpal joint and moving two or more steps in a direction.
Standing	The cow's body is supported by at least three limbs.
Lying	The cow's body isn't supported by any limb; sternum and/or abdomen are in contact with the ground.
Optional activity	Performed in addition to main activity.
Chewing	The cow moves its jaw in grinding movements without having regurgitated before.
Ruminating	The cow regurgitates chews and swallows the cud.
Comfort behaviour	The cow scratches (claw, fence post…) or licks itself.
Social behaviour	The cow interacts with another cow (nosing, rubbing, licking, fighting…).
Explorative behaviour	The cow sniffs or licks an object.
Drinking	The cow's muzzle is in the trough.
Urinating	The cow bends its back and eliminates urine.
Defecating	The cow bends its back and eliminates faeces.
Idle time	The cow is not visible on the video.

Results and discussion

An analysis of two observation days gave a first impression on the distribution of the different behavioural patterns throughout the observed time span and the influence of air temperature and humidity on the behaviour. On day 1 (September) the weather station measured an average temperature of 25.7°C (±2.2) and an average humidity of 39.2% (±9.0) during the observation time; on day 2 (October) average temperature was 13.9°C (±0.6) and average humidity 79.4% (±4.1), respectively. To evaluate the combined influence of air temperature and humidity the Temperature-Humidity-Index (THI) according to Thom (1959) was used. The average calculated THI was 57 (±1) on Day 2 which is categorised as no heat stress. On Day 1 the THI was 70 (±2) on average in the first three observation hours which is categorised as no heat stress as well, whereas the THI was 73 in observation hour five and six (Table 3) which is categorised as mild heat stress. The THI is a reliable method to evaluate the rectal temperature and thereby the heat stress in dairy cows, although, adding more parameters such as wind speed and solar radiation increases the correlation (Dikmen and Hansen, 2009).

Table 3. Average temperature, humidity, THI, wind speed and solar radiation on Day 1 per observation hour

Observation Hour	Temperature (°C)	Humidity (%)	THI	Wind speed (m^*s^{-1})	Solar radiation (W^*m^{-2})
1	22.1	51.57	68	1.3	585.0
2	24.3	45.62	70	1.0	667.8
3	25.0	42.88	71	0.9	713.6
4	26.5	38.87	72	0.8	700.2
5	27.7	29.38	73	0.8	643.3
6	28.2	27.38	73	1.2	527.2

Table 4. Average temperature, humidity, THI, solar radiation and wind speed on Day 2 per observation hour

Observation Hour	Temperature (°C)	Humidity (%)	THI	Wind speed (m^*s^{-1})	Solar radiation (W^*m^{-2})
1	12.9	85.6	55	2.4	176.1
2	13.6	83.0	57	2.2	265.1
3	14.0	79.8	57	2.4	210.8
4	14.2	77.1	58	2.6	274.5
5	14.2	76.9	58	2.6	212.6
6	14.7	74.8	58	1.8	328.6

Figure 1 shows the duration of the main activities (lying, grazing, walking, and standing) for each cow on both observation days. Assessing the main activities in general, all animals spent less time lying and more time grazing, walking and standing on Day 1 compared to Day 2. On average 0.74 h (± 0.57) were spent lying on Day 1 and 2.25 h (± 0.71) on Day 2. These findings correspond to results of other studies on the influence of climate on lying and standing time of dairy cows (Allen *et al.*, 2015; Cook *et al.*, 2007). Solar radiation is an important factor influencing the heat stress of dairy cows as body temperature is lower in cows that have access to shade; although reducing solar radiation by offering shade does not influence the time spent grazing, lying or standing significantly (Tucker *et al.*, 2008). Even though average solar radiation per observation hour was much higher on Day 1 (Table 3 and 4), according to research reports there should not be an influence on the time spent grazing, lying and standing.

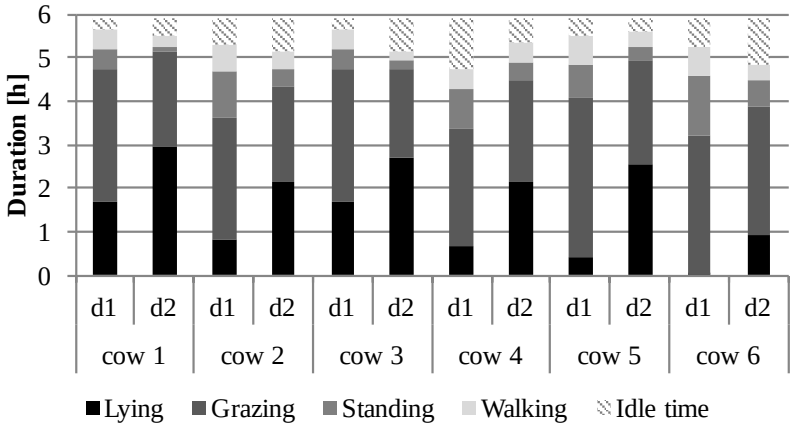

Figure 1. Duration of main activities on observation Day 1 and 2 (definition of activities according to Table 2)

Also the distribution of ruminating on the behavioural patterns lying, standing and walking differs between the two observation days. The total average time spent ruminating amounts to 1.00 h on Day 1 and to 2.10 h on Day 2. On Day 1, 57% of ruminating was done while lying, 40% while standing and 3% while walking, whereas on Day 2 the behavioural pattern of ruminating was shown in 87% while lying, in 12% while standing and in 1% while walking. Other studies support that general rumination time is reduced by heat stress (Tapkı & Şahin, 2006; Karimi *et al.*, 2015). As cows spend more time standing and less time lying when they are stressed by heat, ruminating while standing increased whereas ruminating while lying decreased on days with higher THI. To assess the total time per day spent ruminating observations would have to be extended to nighttime.

Figure 2 shows the time spent ruminating for each cow and observation hour on the two observation days. A certain daily rhythm and herd synchrony is apparent but differs between cows. On Day 1 all cows have a similar rhythm with most of the ruminating taking place in observation hours two to five and no ruminating in observation hour one and six. For Cow 2 and 5 there are two peaks of rumination time, while there is only one peak for Cow 1, 3, 4 and 6. On Day 2, Cow 4 and 5 have similar rhythm with all of the ruminating happening in observation hours one, two and six, whereas Cow 1, 2 and 3 also ruminated in observation hour five. Cow 6 only ruminated in observation hours four and five which results in a higher peak and a different rhythm. Herd synchronisation is a result of various environmental factors, e.g. weather conditions, management and social factors (Benham, 1982) which have to be considered to fully evaluate and understand herd synchrony (Stoye *et al.*, 2012).

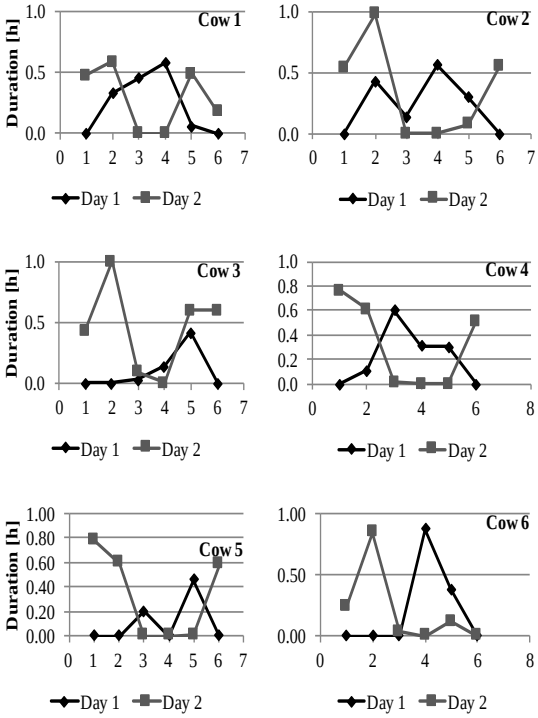

Figure 2. Rumination time per cow and observation hour on Day 1 and 2 (observation hour one started at 10:22 am and observation hours six ended at 4:22 pm)

Conclusions

For the development of algorithms for a monitoring system suitable for grazing situations, THI is a factor that has to be taken into account. On days with high temperatures the time spent lying reduces (Cook *et al.*, 2007). To determine the extent of THI's influence, more observations on days with different temperatures have to be performed. Also other climatic parameters (e.g. wind speed and solar radiation) have to be considered.

The variation between different animals seems to be important for developing reliable algorithms. Even among healthy cows there was a wide range between the duration of the different behavioural patterns. To identify changes in behaviour caused by health disorders or heat, the behaviour of each cow should be compared to its normal behaviour instead of comparing it to the average herd level, which is one way used by the industry (personal communication with smaXtec animal care GmbH, 2018, EuroTier Hannover). Therefore, the algorithms used in the monitoring system should be able to perform machine learning to adjust to each animal individually without having to record all factors influencing the individual behaviour (e.g. milk yield, age, social rank).

Enough data sets, consisting of behaviour and sensor data, were generated by the chosen methods to develop suitable algorithms for the main behavioural patterns in healthy cows. Following this, the algorithms have to be validated by further observations and to detect changes in behaviour caused by health disorders, behaviour and sensor data from days surrounding a disorder in the animals' health (e.g. lameness, mastitis) have to be collected.

Acknowledgements

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References

Allen, J.D., Hall, L.W., Collier, R.J. and Smith, J.F. (2015). Effect of core body temperature, time of day, and climate conditions on behavioral patterns of lactating dairy cows experiencing mild to moderate heat stress. *Journal of Dairy Science*, 98: 118–127.

Augère-Granier, M.-L. (2018). The EU dairy sector. Main features, challenges and prospects, 2018.

Benham, P. (1982). Synchronization of behaviour in grazing cattle. *Applied Animal Ethology*, 8: 403–404.

Cook, N.B., Mentink, R.L., Bennett, T.B. and Burgi, K. (2007). The effect of heat stress and lameness on time budgets of lactating dairy cows. *Journal of Dairy Science*, 90: 1674–1682.

Dikmen, S. and Hansen, P.J. (2009). Is the temperature-humidity index the best indicator of heat stress in lactating dairy cows in a subtropical environment? *Journal of Dairy Science*, 92: 109–116.

Elischer, M.F., Arceo, M.E., Karcher, E.L. and Siegford, J.M. (2013). Validating the accuracy of activity and rumination monitor data from dairy cows housed in a pasture-based automatic milking system. *Journal of Dairy Science*, 96: 6412–6422.

Karimi, M.T., Ghorbani, G.R., Kargar, S. and Drackley, J.K. (2015). Late-gestation heat stress abatement on performance and behavior of Holstein dairy cows. *Journal of Dairy Science*, 98: 6865–6875.

Reiter, S., Sattlecker, G., Lidauer, L., Kickinger, F., Öhlschuster, M., Auer, W. *et al.* (2018). Evaluation of an ear-tag-based accelerometer for monitoring rumination in dairy cows. *Journal of Dairy Science*, 101: 3398–3411.

Rutten, C.J., Velthuis, A.G.J., Steeneveld, W. and Hogeveen, H. (2013). Invited review. Sensors to support health management on dairy farms. *Journal of Dairy Science*, 96: 1928–1952.

Stangaferro, M.L., Wijma, R., Caixeta, L.S., Al-Abri, M.A. and Giordano, J.O. (2016a). Use of rumination and activity monitoring for the identification of dairy cows with health disorders. Part I. Metabolic and digestive disorders. *Journal of Dairy Science*, 99: 7395–7410.

Stangaferro, M.L., Wijma, R., Caixeta, L.S., Al-Abri, M.A. and Giordano, J.O. (2016b). Use of rumination and activity monitoring for the identification of dairy cows with health disorders. Part II. Mastitis. *Journal of Dairy Science*, 99: 7411–7421.

Stangaferro, M.L., Wijma, R., Caixeta, L.S., Al-Abri, M.A. and Giordano, J.O. (2016c). Use of rumination and activity monitoring for the identification of dairy cows with health disorders. Part III. Metritis. *Journal of Dairy Science*, 99: 7422–7433.

Statistisches Bundesamt (2019). Statistisches Bundesamt Deutschland - GENESIS-Online. https://www-genesis.destatis.de/genesis/online/data (last accessed February 26, 2019).

Stoye, S., Porter, M.A. and Stamp Dawkins, M. (2012). Synchronized lying in cattle in relation to time of day. *Livestock Science*, 149: 70–73.

Tapkı, İ. and Şahin, A. (2006). Comparison of the thermoregulatory behaviours of low and high producing dairy cows in a hot environment. *Applied Animal Behaviour Science*, 99: 1–11.

Thom, E.C. (1959). The Discomfort Index. *Weatherwise*,12: 57–61.

Tucker, C.B., Rogers, A.R. and Schütz, K.E. (2008). Effect of solar radiation on dairy cattle behaviour, use of shade and body temperature in a pasture-based system. *Applied Animal Behaviour Science*, 109: 141–154.

Tullo, E., Fontana, I., Gottardo, D., Sloth, K.H. and Guarino, M. (2016). Technical note: Validation of a commercial system for the continouous and automated monitoring of dairy cow activity. *Journal of Dairy Science*, 7489–7494.

Development of educational VR simulator of livestock houses

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Abstract

Along with the advancement on livestock industry in South Korea, problems concerning the maintenance of micro-climate inside the facility arise. These problems were further intensified when airflow is taken into consideration. The airflow is the main mechanism of internal environmental distribution such as gas, temperature, humidity and dust. However, this parameter is invisible and difficult to predict and measure. Thus, many consultants as well as farmers have misunderstood and made wrong judgements on ventilation efficiency and internal airflow distribution. Therefore, it is essential to develop an educational material for the farmers to visually recognise micro-climate condition. In this study, aerodynamic approach was carried out using CFD (computational fluid dynamics) combined VR (virtual reality) technology. First, several research papers, reports, journals, and publications on livestock industry have been reviewed to identify major problems inside swine houses during hot and cold seasons. Then, open-source CFD was used for computing the selected problems and their solutions. These CFD computed results, such as airflow, temperature, humidity and gas, were applied to VR simulator for educating swine farmers.

Keywords: virtual reality (VR), livestock, CFD, micro-climate

Introduction

Livestock facilities in South Korea have become larger and more automated to satisfy the demand of consumers. Enlargement of these facilities makes it difficult to keep the micro-climate uniform and suitable for growing pigs. Non-uniform micro-climate can result in poor environment causing stress to the livestock. These stresses could weaken immune systems of the animals and may result in death (Myer & Bucklin, 2007). Various field experiments have been conducted to determine the optimum micro-climate in swine (Myer & Bucklin, 2007; Wang, Zhang, Riskowski, & Ellis, 2002). Despite the effectivity of field experiments, there have been limitations such as: 1) time- and labour-consumption problems; 2) various environment condition changes and; 3) representation of measured values. Because of these limitations, obtaining results from field experiments is difficult. Recently, computational fluid dynamics (CFD) have been widely used for analysis of air flow, temperature, humidity, gas and dust concentration in various environmental conditions (Bartzanas, Kittas, Sapounas, & Nikita- Martzopoulou, 2007; Bjerg, Lee *et al.*, 2002, 2004, 2009; Seo, Lee, Kwon *et al.*, 2009). However, despite its accurate and reliable output, livestock farmers and consultants cannot easily grasp the meaning of the computed results. Therefore, educational technology, which can effectively display the aerodynamic results, is necessary to help maintain optimum micro-climate in livestock facility.

Virtual reality (VR) technology that can offer virtual experience of invisible things has been developed and used in various fields. The VR industry gained its popularity in many fields of interest such as fire-fighting, entertainment and medicine. Through this technology, users can make better decisions since they can clearly understand and visualise the environment they are studying.

In this study, aerodynamic approach was carried out using CFD (computational fluid dynamics) combined with VR technology to create educational materials for target audience.

Material and methods

Experimental swine house

In South Korea, most mechanically ventilated nursery houses are constructed based on 2009 Korean Standard of swine houses (Korea Pork Producers Association, 2009) whereas some of the fattening swine houses are naturally ventilated via winch curtain openings. Due to distinctive seasons in the country, maintaining the optimal environment is a laborious task for farmers. In this study, a standard nursery swine house was chosen as the experimental room for simulation. The size of the experimental room was 5.5 m wide, 9.0 m long, and 2.4 m high, as shown in Figure 1.

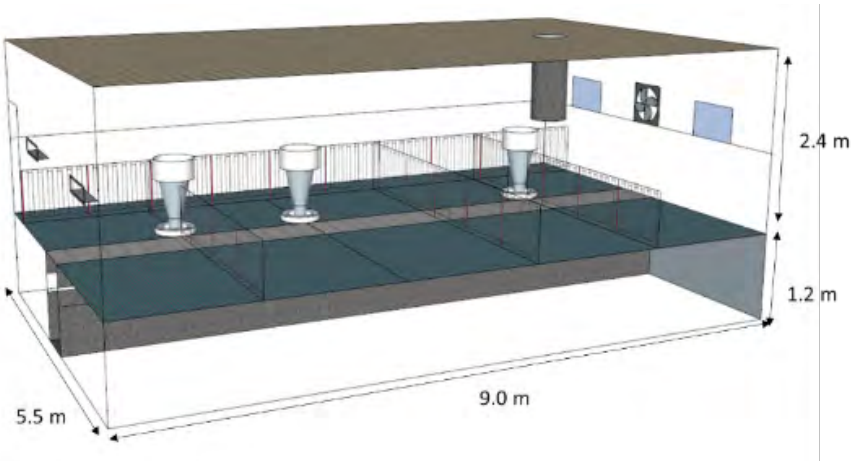

Figure 1. Schematic diagram of the experimental nursery swine house

Computational fluid dynamics (CFD)

CFD is a numerical method for computing the behaviour of fluids by solving a nonlinear partial differential equation, such as the Navier-Stokes equation, based on the principles of mass conservation, Newton's second law, and the first law of thermodynamics. CFD has been used as a powerful tool in the field of agriculture for micro-climatic analyses of livestock houses, as well as studies on the dispersion of livestock odour and aerosols (Launder and Spalding, 1974). CFD analysis is a technique that numerically solves equations based on the finite volume method (FVM), which consists of three design stages. In the pre-processing stage, the physical shape of the target area is designed, on which its grid mesh is generated. In the main processing stage, each governing equation for the physical phenomena is discretized and solved. A qualitative and quantitative analysis of computation results is conducted in the post-processing stage. Software discretizes and solves the Navier-Stokes equations for the conservation of mass, energy and momentum regarding the transport of fluid and energy.

Virtual Reality (VR)

Virtual reality (VR) refers to computer technologies that use virtual reality headsets to generate realistic images, sounds and other sensations that replicate a real environment or create an imaginary setting. At present, research using VR technology focuses on practical

application and industrialization based on ICT. The importance of realising micro-climate in livestock facilities is to maintain a suitable environment. Through this method, the invisible air and heat flow can be visualised. VR technology is a helpful tool to develop training materials for the farmers. An example of virtual reality headset is shown in Figure 2.

Figure 2. Equipment of virtual reality simulation (Usman, 2016)

Development of CFD simulation model

Design-modeler software (Release 16.1, ANSYS Inc, U.S.A) was used to design the 3-D computational domain with meshes, including the specific configurations of the different components of the experimental swine house. The designed mesh domain, as shown in Figure 3, was exported to OpenFOAM (version 2.1.1), which is the main-solver for the numerical calculation which uses the CFD technique that solves the Navier-Stokes equations with Reynolds theory for all meshes in the computational domain. Based on previous study, validated model was used in this study (Seo *et al.*, 2009; Kwon *et al.*, 2016). Therefore, turbulence model was determined as RNG k-ε and grid size was determined as 0.1 m based on grid independence tests. Presented in Table 1 is the statistical information of mesh model and the initial environment condition.

Table 1. Statistics data of mesh and environment condition

Contents	Values
Model size	5.5 m width; 9.0 m length; 2.5 m height
Shapes of mesh	Tetra, Multi-zone
Number of meshes	6,107,109
Orthogonal quality	Min 0.219 > 0.01
Skewness	Max 0.850 < 0.95
Outdoor temperature	264 K (cold season), 304 K (hot season)
Velocity outlet (total)	0.9 m/s (cold season), 15.5 m/s (hot season)
Pig surface temperature	313 K

Investigating main problems

To investigate the main problems of swine houses, several research papers, reports, journals, and publications on livestock industry have been reviewed to identify major problems in swine houses during hot and cold seasons in South Korea. A total of 63 papers

and 14 journals were investigated and summarised to obtain the appropriate initial simulation environment conditions. The major problems of swine houses are divided into two categories. First, in cold season, there are cold stress, internal non-uniformity, insufficiency of ventilation rate, high gas and odour concentration, etc. Second, similarly during the hot season, major problems of swine houses include temperature stress, internal non-uniformity, excessive flow rate, rearing density, etc. Maintaining proper micro-climate, ventilation should be done properly according to the environment and seasonal changes. Since many farmers do not fully understand the air flow inside the livestock houses they fail to maintain the proper micro-climate during cold season causing the swine to lose their immunity. Similarly, in hot season, maximum ventilation is provided but excessive air flow can create a negative effect on swine. To solve these problems, aerodynamic approaches should be considered to control micro-climate in swine houses.

Combination of CFD simulation and virtual reality

CFD calculation was performed based on the identified problem from the review. These results show air flow, gas concentration, and temperature distribution in the swine house. However, these CFD results may be difficult for farmers to understand. Therefore, it is necessary to create visualised educational materials based on the computed results. Since the exported data have a lot of grids, they could be overloaded on virtual reality simulation. A point has data like temperature, x-velocity, y-velocity, z-velocity, vector, humidity, NH_3 concentration in each grid. The points in the CFD domain are located at intervals of 10 cm. The position of points will be modified to use in virtual reality program. Each point will be streamlined to visualise the air flow. VR cold equipment shows satisfactory simulation of the micro-climate in the virtual reality simulation.

Results and discussion

CFD simulation results

One serious problem inside the nursery house during cold season is the direct inflow of cold air through side slot. Figure 3-(a) shows the temperature and direction of inflow air during this period. Difficulties on measuring the inside temperature at this stage may account to the non-uniformity of inside air temperature. The measure air temperature near the slots was about 274 K, while the average temperature of center was about 301 K. This temperature is far lower than the appropriate temperature for piglets. Also, as shown in Figure 3-(a), ammonia gas has accumulation increases as the distance from the side slots increases. This means that the fresh air could not reach any other part of the facility. These problems however can be solved by adjusting the air inlet angle. When the inlet angle is adjusted to 45 degrees at the side slot, the inflow air rises to the top and falls down to the piglet, as shown in Figure 3-(b). Since the risen air relatively mixes more with upper warm air, the difference between inflow air temperature and indoor temperature could be reduced to about 2-3 K. In cold season, however, the ventilation rate is low, so the inflow air does not stay long on top. The air temperature is still unsuitable and non-uniformity for nursery swine. Also, this modified structure cannot remove ammonia gas sufficiently. An alternative way would be to make a hole on the ceiling to avoid inflowing cold air and to improve internal uniformity (Figure 3-(b)). The cold air stays in the ceiling to warm up and it slowly flows out through small holes. In the hot season, the air temperature in the ceiling is lower than outside. It could help to prevent hot-air-inflow from outside directly.

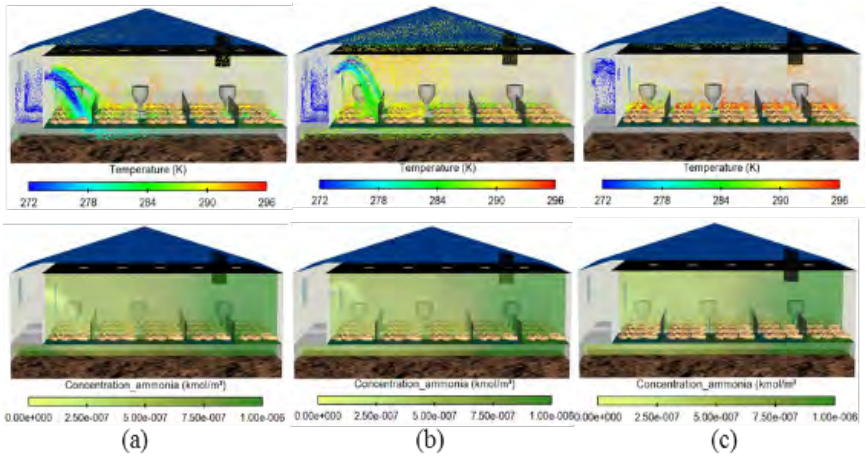

Figure 3. Temperature (top row) and concentration of ammonia (bottom row) by using side slots (left column), modified side slots (middle column) and ceiling holes (right column)

Design of simulator model

Representation of pig house equipment inside the building and the pig model should be properly made to accurately imitate the real-life scenarios. Realistic simulation depends on the number of polygon which is closely related with resolution of the model geometry. If the model has so many polygons, virtual reality equipment cannot drive the heavy simulation and may cause system lagging. In most cases, it can also cause dizziness to the user. On the other hand, low polygon model looks too simple and unrealistic. As shown in Figure 4, if 3D piglet model has a lot of polygon, the VR simulator requires more time to calculate. Thus, there is a need to modify the polygon data. Consequently, for VR simulator, middle poly model was chosen as a VR simulation model.

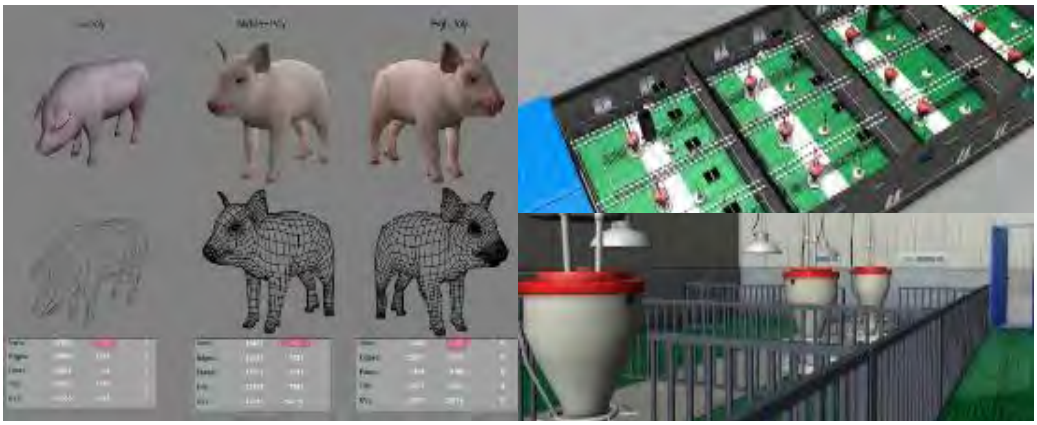

Figure 4. The comparative data of pig model quality (left) and the views of nursery house in virtual reality simulation (right)

Development of VR simulator

To combine CFD simulation data with VR simulator, it is necessary to determine same data point to display same contour or vector field in virtual reality simulation. In CFD

simulation results, there are as many points as grid numbers. However, virtual reality hardware performance is not enough to fetch such huge data. If the data is too large, it will need a lot of frames for simulation. Eventually it causes motion sickness to the user. Therefore, the distance between points should be modified to reduce the total number of points. To find optimal distance, 0.05 m, 0.1 m, 0.15 m, and 0.2 m were used in the test. From this, it was found that 0.1 m was the best optimal distance. Each point has their own data like temperature, magnitude of velocity, direction, gas concentration, etc. In virtual reality, simulation, visualised air flow streamline, temperature, gas concentration was presented by contour and vector field.

In the next step, virtual reality simulator which provides micro-climate information for educating farmers, will be developed with various cases. In order to obtain sufficient data, various cases must be computed by CFD. Each case has a different structure, environment condition and ventilation system. Because each case takes considerable computation time, computation should proceed with the most typical problems.

Figure 5. Various examples of the application of virtual reality technology on fluid (Hynek *et al.*, 2005; Kelly, 2016)

Conclusion

In this study, aerodynamic approach was carried out using CFD combined with VR technology to develop educational materials for general use. To investigate the representative problems inside the swine houses, related studies have been reviewed. Through the developed VR simulator, farmers and consultants can receive effective education in a three-dimensional VR space. This way they can experience the internal airflow and various environmental factors according to the ventilation type and operation. Users can also experience a variety of methods to improve the problems in VR simulator. Through the UI, considering the accessibility and convenience of the user, the VR simulator can be used variously such as farmers, consultants and students. For the future study, development of higher resolution simulator to the computer results must be prioritised with improved computer resources, higher quality model and structural configurations including the detail resolution could be considered. Also, more cases should be computed by CFD for various training situations.

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References

Bartzanas, T., Kittas, C., Sapounas, A.A., & Nikita- Martzopoulou, Ch. (2007). Analysis of airflow through experimental rural buildings: sensitivity to turbulence models. *Biosystems Engineering*, 97: 229–239.

Bitog, J.P., Lee, I.B., Hwang, H.S., Shin, M.H., Hong, S.W., Seo, I.H., *et al.* (2012). Numerical simulation study of a tree windbreak. *Biosystems Engineering*, 111(1): 40–48.

Bjerg, B., Svidt, K., Zhang, G., Morsing, S., & Johnsen, J.O. (2002). Modeling of air inlets in CFD prediction of airflow in ventilated animal houses. *Computers and Electronics in Agriculture*, 34: 223–235.

Hynek,, Bryden, Richard. (2005). Potential applications of virtual engineering to swine production systems. *American Society of Agricultural Engineers.* 701P0205

Kelly Maes. (2016). Zorgt Virtual Reality voor een transformative binnen de verzekeringswereld. Linked in journal.

Korea Pork Producer Association. (2009). 2009 Korean Standard of swine.

Kwon, K., Lee, I., Zhang, G.Q., & Ha, T. (2015). Computational fluid dynamics analysis of the thermal distribution of animal occupied zones using the jet-drop-distance concept in a mechanically ventilated broiler house. *Biosystems Engineering*, 136: 51–68.

Kwon, K,. Lee, I., Ha, T. (2016). Identification of key factors for dust generation in a nursery pig house and evaluation of dust reduction efficiency using a CFD technique. *Biosystems Engineering*, 151: 28–52.

Launder, B., & Spalding, D. (1974). The numerical computation of turbulent flows. *Computer Methods in Applied Mechanics and Engineering*, 3(2): 269–289.

Lee, I., Park, W., Yu, B., Yun, J., Chun, J., Kim, K., Cho, H. (2002). Optimum design of forced ventilation system of piglet house using computer simulation. *2002 ASAE Annual International Meeting/CIGR XVth World Congress*. Paper number 024109.

Lee, I.-B., Sase, S., Han, H.-T., Hong, H.-K., Sung, S.-H., Hwang, H.- S., *et al.* (2009). Ventilation design for a chick incubator using computational fluid dynamics. *JARQ*, 43(3): 227–237.

Lee, I.-B., You, B.-K., Kang, C.-H., Jeun, J.-G., Kim, G.-W., Sung, S.- H., *et al.* (2004). Study on forced ventilation system of a piglet house. JARQ, 38(2): 81–90.

Myer, R.O., & Bucklin, R.A. (2007). Influence of rearing environment and season on growth performance of growingfinishing pigs. *Transactions of the ASABE*, 50(2): 615–620.

Seo, I.-H., Lee, I.-B., Kwon, S.-H., Hwang, H.-S., Hong, S.-W., Bitog, J.P., *et al.* (2009a). Numerical investigation of the pig house to prevent pig respiratory disease according to ventilation system. *In The 2009 CIGR international symposium of the Australian society for engineering in agriculture*. Brisbane, Queensland, Australia: The Chifley at Lennons.

Usman Prizada. (2016). AMD reveals list of qualified FX series processors for an Oculus Rift 'VR-Ready' PC build. WWFTECH journal.

Wang, X., Zhang, Y., Riskowski, G.L., & Ellis, M. (2002). Measurement and analysis of dust spatial distribution in a mechanically ventilated pig building. *Biosystems Engineering*, 81(2): 225–236.

SAFTIR - a novel point-of-need diagnostic platform for animal health and food safety

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Abstract

This paper introduces a portable rapid molecular diagnostics device concept based on unique and novel SAFTIR (Supercritical Angle Fluorescence and Total Internal Reflection) optical transducer technology. The device platform is compatible with numerous fluorescence assay chemistries for performing rapid tests on-site. The SAFTIR technology has been developed at VTT Technical Research Centre of Finland utilising our know-how in biosensors, integrated optics, electronics and biosensor prototyping. The uniqueness of the SAFTIR prototype device is based on the novel measurement principle involving integrated optical elements and waveguides on the disposable test strip and the specific reader device with proper interface optics. At concept level, SAFTIR has a lot of similarities with the Lateral Flow Assay (LFA) based rapid tests by consisting of an analyte specific disposable test strip and a special reader device. However, in technical details, there are significant differences and benefits, namely SAFTIR utilises surface-bound fluorescence detection principle ensuring high sensitivity with an excellent signal-to-noise ratio, fast response time and minimal sample matrix effects. In this paper, we present for the first time the integrated SAFTIR device concept, portable prototype and development aiming at smart farming applications. The initial application focus is on-site detection and quantitation of mycotoxins for both arable and livestock farming. The reference and starting point is a previously developed assay based on a recombinant anti-immunocomplex antibody for HT-2 mycotoxin detection.

Keywords: molecular diagnostic, rapid test, fluorescence assay, mycotoxin, HT-2

Introduction

Typical successful adoption of sensors in agriculture relies on the robust, field-usable, connected and distributed devices, which should also provide high performance with low cost. The sensor data, and especially extracted information from the data to the farm management systems, should provide important value to farmers directly or through the companies providing services to them. The sensors and data sources for various biomarkers, contamination and pathogens are especially valuable in farm management by providing direct relation to actions and predictions to control animal health and food safety. This information often has high impact on farm productivity by reducing losses. However, from the field-usable sensor technology point of view, the molecular diagnostics area is especially demanding. The analyte species are often in very low concentrations and sample matrices are complex. Thus, specificity and sensitivity requirements are often difficult to meet without tedious sample treatment and analysis procedures that often requires special chemistry skills that are not typically available on farms.

The digitalization trend and opportunities for precision farming supports designing the on-site novel sensor solutions with immediate digital data access, meaning practically utilizing IoT connected digital readers instead of only user observation based qualitative colour-indicator-type test strips. There are several digital rapid test solutions on the market that are purportedly useful in on-farm or on-site applications. The main stream

is Lateral Flow Assay (LFA) tests employing camera-based optical readers as data access, such as mycotoxin rapid test kits and readers offered by companies like R-Biopharm and Rohmer Labs.

This paper presents the SAFTIR rapid test technology concept and early-stage prototype development, which is aimed at agritech applications by offering a robust and convenient to use interface, having fast response times and focusing only on digitalised data access. We have identified several practical point-of-need diagnostics needs for on-farm use. In this paper, we focus on mycotoxins. Consumption of mycotoxin-contaminated food or feed can cause acute or chronic toxicity in human and animals. Some mycotoxins are lethal (e.g. HT-2) even in low concentrations. Mycotoxins are the secondary metabolites produced by certain filamentous fungi (molds). They can enter our food chain either directly from plant-based food components contaminated with mycotoxins or by indirect contamination from the growth of toxigenic fungi on food. They are naturally occurring and practically unavoidable. Therefore, it is justified that truly field-usable and reliable on-site detection and identification of mycotoxins helps to mitigate risks and prevent losses in both arable and livestock farming (Bryden, 2012).

For the starting point of the novel sensor technology evaluation, we selected HT-2 mycotoxin as an analyte. HT-2 toxin is a secondary metabolite of *Fusarium* spp. fungi and has very high toxicity and thus a need for high sensitivity of detection. Furthermore, the HT-2 recombinant antibody has been developed in our earlier projects and, therefore, offers a good benchmark and reference know-how to evaluate the new sensor technology (Arola *et al.*, 2016).

SAFTIR transducer principle and background

The SAFTIR optical transducer system utilises simultaneously both the total internal reflection (TIR) excitation and supercritical angle fluorescence (SAF) detection principles and has been demonstrated earlier for narcotics analysis with different set-ups by Välimäki and Tappura (2009) and Välimäki *et al.* (2010). The combination of these two detection principles enables high sensitivity and selectivity through surface-bound fluorescence phenomena, an excellent signal-to-noise ratio and fast measurements with effective background suppression.

The proposed portable system integrates the fluidic elements for the liquid sample transport and the optical sensing elements (incl. waveguides and e.g. diffractive lenses or other light directing/guiding structures) in/on a single test strip (Figure 1). The measurement principle is illustrated in Figure 2. Integrated waveguides are applied to transmit light to the targets (to the points of measurement), while the excitation of the fluorescence labels is performed by the evanescence field of the total internal reflections extending into the sample only to the very vicinity of the slide-sample interface where the target molecules are attached. The fluorescence emitted into the half-space of the slide (to the medium of the higher refractive index) at or above the critical angle of the total internal reflection – i.e. the fluorescence stemming only from the very vicinity of the interface – is collected by applying diffractive optical elements (lenses) or other integrated structures facilitating the collection of light emitted to the desired angles.

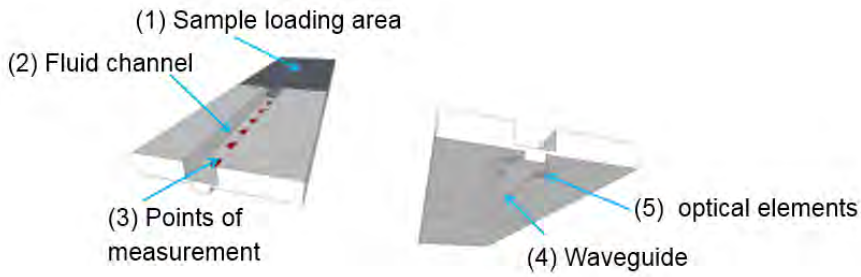

Figure 1. SAFTIR test strip design principle

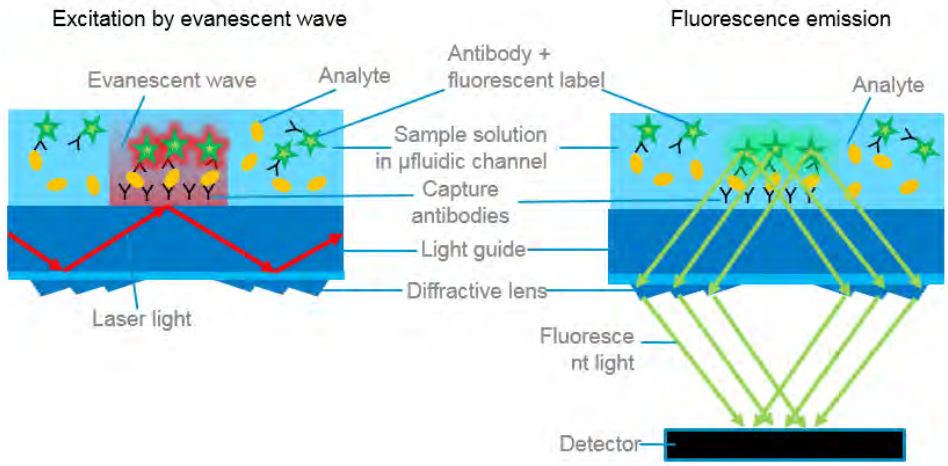

Figure 2. SAFTIR transducer principle in the opto-fluidic system (cross sectional view from the end of the waveguide)

Material and methods

Reader and test strip design

For the portable SAFTIR device implementation, several optical modelling tools were employed. The readout device was designed using the Optics Studio non-sequential design tool for excitation laser 633 nm, emission/filter 670/40 nm. Simulated angular distributions in various test strip materials were modelled as a pointwise defined radial source. The SAF emission distributions were calculated and optimised for a randomly oriented dipole located at different distances from the solid-liquid interface at the bottom of the fluidic channel following the presentation of Enderlein *et al.* (1999).

Assay chemistry testbed

Assay chemistry development was carried out with plasma treated 96-well Polystyrene plate (Thermo 269620), scanned with TECAN LS400 confocal laser scanner (ex laser 633 nm, em filter 670/40 nm) where HT-2 standards were added in 50 µl of *Assay buffer* [Alexa Fluor 647-labelled anti-HT2 immunocomplex antibody; in PBS]. Capture antibody was spotted in 8 replicate spots (antibody density 6.25 ng/mm^2). The testbed system is illustrated in Figure 3.

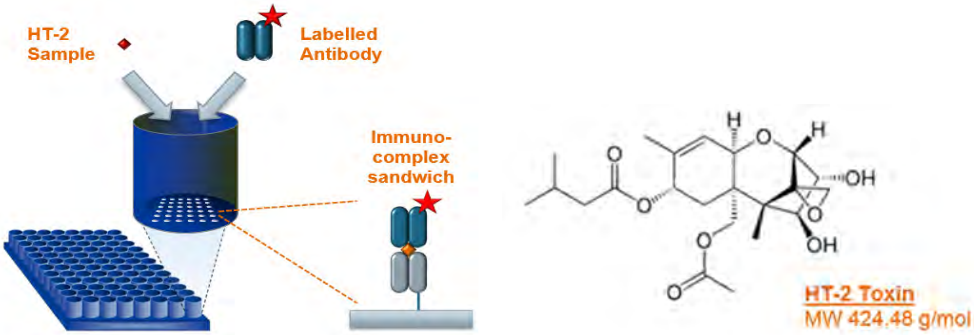

Figure 3. Schematic illustration of assay chemistry development testbed for HT-2 toxin analyte

Results and discussion

SAFTIR device optical and mechanical design outcomes

The developed prototype concept design is illustrated in Figure 4. In order to protect the emission reader optics from ambient light, a light blocking cover is used on top of the test strip. Liquid sample is dispensed via hole in the cover to the precisely aligned fluidic inlet of the test strip (Figure 5).

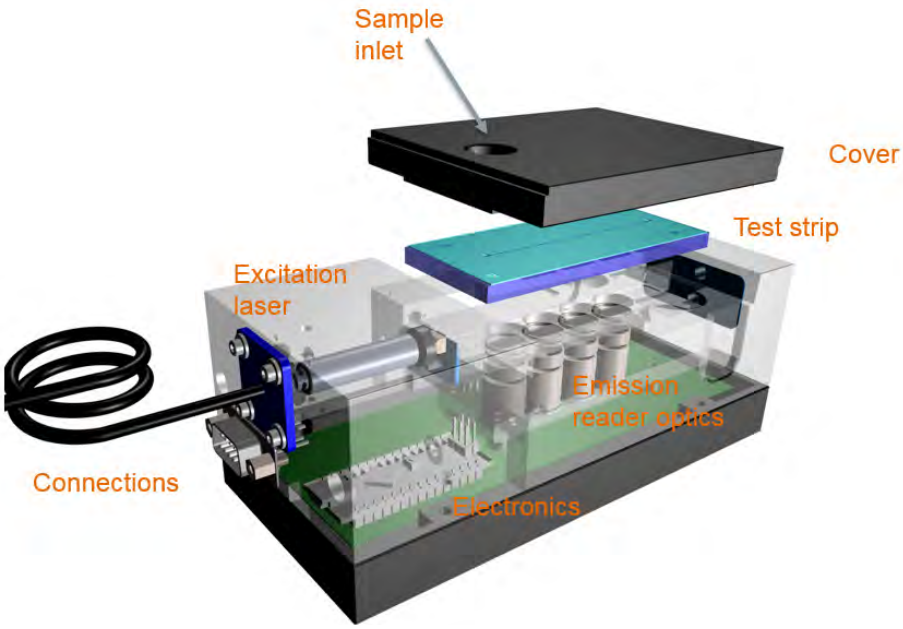

Figure 4. Developed reader device utilizing SAFTIR measurement principle

At this stage, the prototype design was aiming at maximising the optics sensitivity. The readout optics simulations showed that the SAF angles higher than 57.5 degrees can be measured with the integrated measurement platform and that the overall SAF collection efficiency would be about 30%. The relatively wide excitation channel used in the current design together with the restricted strip thickness limit the collection efficiency.

SAFTIR test strip

The base of the test strip is made by injection molding compatible and mass-producible material, which have transparency for the selected excitation and emission wavelengths. Based on the modelling and assessment, we selected polystyrene as it meets the requirements optimally. The test strip design is illustrated in Figure 5. The core parts also involve two layers of patterned tapes (lid and fluidic layers). The fluidic layer defines the dimensions of the fluidic channel. At this design those are: width 1 mm, length: 65 mm and height: 90 µm. The optical base strip consist of four measurement points on the top of individual emission reader optics. The assay chemistry shall be employed to the base strip before final assembly of the tape layers. The four measurement points allow variabilities such as multianalyte tests, reference test points, concentration range enhancement or self-diagnostics approaches.

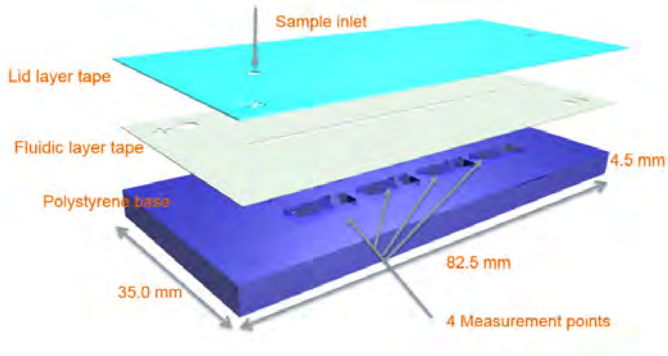

Figure 5. SAFTIR test strip layout and dimensions

HT-2 assay chemistry

Before employing the assay on the test strip, several assay development steps need to be carried out in the laboratory testbed. Assay performance depends on various factors, such as type of assay (in this study it is immunocomplex assay for HT-2, Figure 3), selected fluorescence labels, surface chemistry tailoring methods, binding agents, wetting agents, measurement spot size and amount of antibody. Present testbed system is useful for optimisation as it provides efficiently data from various parameters and their precision. Figure 6 illustrates testbed response data where the parameter is surface density of the antibody.

As shown in Figure 6, the response depends strongly on the surface density of the immobilised capture antibody. Apparently, 7.7 ng/mm^2 is the optimum when it comes to high sensitivity and linear response in the applied HT-2 concentration range of 0-200 ppb. An attempt at higher surface density results in lower response signal and unstable molecular surface consistency. On the other hand, lowering surface density leads to rapid deterioration of the sensitivity. The careful optimisation of the antibody density on the polystyrene surface probably leads to the molecular arrangement of the antibodies as a semi-monolayer. A monolayer would probably also improve the performance of the surface-sensitive SAFTIR detection. Tailoring of the capture surface enables the modification of the system response towards a wider range of analyte concentrations, which can be accomplished, e.g. using multiple, differentially responsive test points on the same test strip. The expected HT-2 detection limit in the SAFTIR concept is estimated to be below 0.5 ppb.

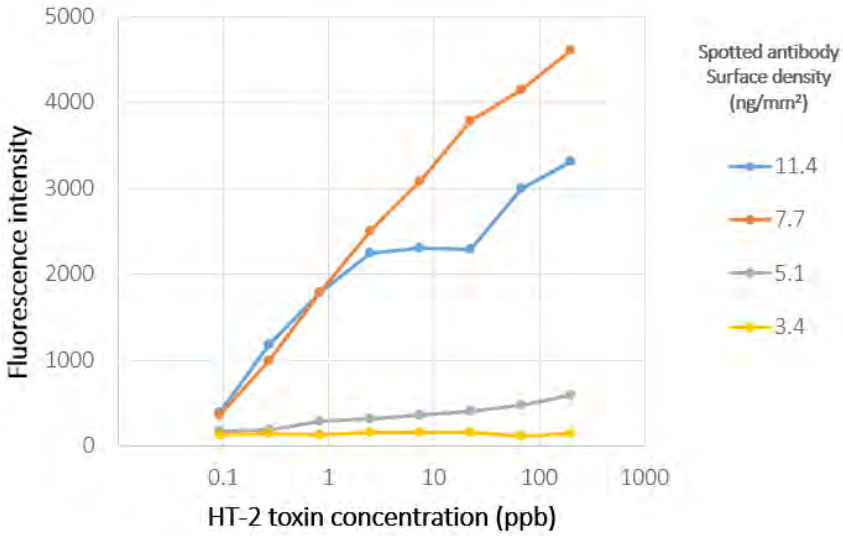

Figure 6. Fluorescence intensity (response) as a function of HT-2 toxin concentration in laboratory reference solution in various HT-2 antibody densities applied on the measurement spot in the assay chemistry testbed

Conclusions

This paper proposed a novel portable rapid-diagnostic test device concept and platform for on-farm uses for biomarkers. The robust design has variables for different application requirements such as assay chemistry, surface-bonding and optical component designs. These inherent variables enable to tailor the sensor response e.g. in relation to the requirements of quantitation accuracy and/or lower limit of detection. The platform and the development tools enable the system to be tailored for new applications. Further studies will be conducted to demonstrate the performance with various assays and develop the system technical readiness.

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References

Arola, H.O., Tullila, A., Kiljunen, H., Campbell, K., Siitari, H. and Nevanen, T.K. (2016). Specific Noncompetitive Immunoassay for HT-2 Mycotoxin Detection. *Anal. Chem.*, 88(4): 2446–2452.

Bryden, W.L. (2012). Mycotoxin contamination of the feed supply chain: Implications for animal productivity and feed security. *Animal Feed Science and Technology,* 173: 134–158.

Enderlein, J., Ruckstuhl, T. and Seeger, S. (1999). Highly efficient optical detection of surface-generated fluorescence. *Appl. Optics,* 38: 724.

Välimäki, H. and Tappura, K. (2009). A novel platform for highly surface-sensitive fluorescent measurements applying simultaneous total internal reflection excitation and super critical angle detection. *Chemical Physics Letters,* 473: 358–362.

Välimäki, H., Pulli, T. and Tappura, K. (2010). Applying total internal reflection excitation and super critical angle fluorescence detection to a morphine assay. *Journal of Fluorescence* 20, pp 1003–1008.

Development of a PLF tool in order to assure welfare conditions for growing pigs

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Abstract

The application of different technological innovations in the intensive systems of pig production has generated some problems related to health and animal welfare. The animal welfare can be measured with indicators capable of expressing the animals' adaptability to the environment. Temperature is one of the main components of the environment, since it influences the physiology, behaviour and productivity of the pigs. The first phase of this study aims to verify the adaptive evolution to different environmental conditions (summer, thermoneutrality and winter) in growing and fattening pigs. Seven females (initial weight: 45 kg) were used. The animals were housed in a room equipped with an environmental control system. The environmental data collected were temperature and relative humidity. The physiological parameters measured were surface and rectal temperature. The feed intake was monitored through an individual feed machine. In order to monitor the behaviour of animals, video cameras and microphones were installed. The final weight of the animals was about 95 kg. Respectively in summer, thermoneutrality and winter, the daily food intake was 2.111 kg day^{-1}; 2.473 kg day^{-1}; 2.814 kg day^{-1} and the average daily gain was 0.768 kg day^{-1}; 0.923 kg day^{-1}; 0.808 kg day^{-1}. The corresponding values of surface temperature were 36.2 °C; 33.6 °C and 35.2 °C and of body temperature were 38.9 °C, 38.7 °C and 38.4 °C.

In order to validate the methodology and some results, the second phase of the project will be in a commercial farm, where the animals are submitted to real conditions.

Keywords: PLF, animal welfare, environmental control, pigs

Introduction

The new global requirements of agricultural production, within the ethical process, are increasingly turning to the concepts of good production practices, considering animals and workers welfare, food safety and respect for the environment (Campos, 2009, cited by Baêta & Souza, 2010). On the other hand, it is estimated that in the year 2050, the world population will grow to 9.8 billion people, compared to the present 7.6 billion (Mota, 2018); this will increase the demand for food and animal products (Godfray *et al.*, 2010).

Facilities and their equipment should protect animals from adverse conditions, as well as provide adequate comfort and welfare with appropriate levels of ventilation, temperature and humidity (Baêta & Souza, 2010). In this sense, intensive pig farms are in a phase of change.

The environmental conditions have a great impact on the productivity of different animal species, especially in poultry and swine industries, that usually work under intensive systems (Cruz & Baptista, 2006).

In intensive systems, animal comfort and welfare suffer directly from the environment, causing difficulties in maintaining thermic balance inside the facilities, in the form of natural behaviours which affects the productive and reproductive performance of the swine (Pandorfi, 2006).

In order to reach the optimal environmental conditions, the livestock facilities must have a monitoring and a control system. However, there is a need for modern facilities to not only monitor the environmental conditions, but also the behaviour and health of the animals (Banhazi & Black, 2009; Koenders *et al.*, 2015).

Animal welfare indicators provide the necessary information to assess welfare and to improve it so we can measure animal welfare by productive, sanitary, behavioural and physiological indicators (Candiani *et al.*, 2008). In this evaluation of animal welfare, we can't use only one indicator, a set of indicators must always be considered when measuring animal welfare.

Precision livestock farming can be defined as the application of technological principles and engineering processes to the farm management (Wathes *et al.*, 2008). This tool has the potential to improve animal welfare and increase productive outcomes (e.g. weight gain) (Koenders *et al.*, 2015), as well as to detect, in real time, certain behaviours of the animal that could indicate its level of welfare. Early detection, possible through real-time monitoring, can minimise production costs by reducing the incidence of diseases and mortality (Nasirahmadi *et al.*, 2017).

The goal of AWARTECH Project is to develop a new tool that responds in real time to the environmental needs of animals through physiological, behavioural and productive indicators. In other words, our final goal is to have a platform that, through the animal, will make it possible to control all the environmental parameters (temperature, humidity, gas concentration, air speed).

Materials and methods

The project began with the small lab prototype. We submitted the animals to different environmental conditions to test animal adaptation/stress. In order to measure this adaptation, we used several indicators like physiological (e.g. temperature of the animal), behavioural (e.g. lying patterns) and productive (e.g. growth rate). In addition, we control the interior environmental conditions and test the interconnection between all the collected data in order to adjust the environment according to animal responses in an automatic and real time basis – the technologic platform of the project.

Animals, Housing and Equipment

Seven crossbred (Topigs Norsvin (TN60) x Pietrain) growing gilts were used in this study. The animals were randomly selected from a commercial farm and transferred to the experimental farm of Mitra in Évora. The initial body weight was around 45 kg and they were housed in one pen with an area per animal of 1.5 m^2. This room was equipped with an environmental control system.

All gilts were identified with an RFID ear tag. The experiment started after two weeks of adaptation to the room, environment and human presence. During this period, the food was provided in *ad libitum*, with a standard commercial diet and free access to water. During this period, the gilts were trained to be accustomed to saliva sampling. In these days of adaptation, the environmental control system was set to thermoneutrality, the temperature was 18 ± 2 °C and relative humidity was 60%.

The room was equipped with sensors of temperature (T) and relative humidity (RH). The sensors collected the data at every hour. To monitor the behaviour, cameras and microphones were also installed. The food was provided to the animals with an individual automatic feed machine (schauer compident MLP II) that had one scale for the food and another for the animals. The machine was provided with an electronic identification system that was activated by the RFID ear tag. The feeding machine was connected to a computer that recorded and saved the data (feed intake and animal weight).

Experimental Design

The experimental period of each condition was 13 d. We have simulated three different environmental conditions: winter (W) – cold stress, thermoneutrality (TN) and summer (S) – heat stress. The control system allowed us to make a variation of the temperature and the humidity. We set up the control system for summer with T: 30 ± 2 °C, RH: 50%; thermoneutrality with T: 17 ± 2 °C, RH: 60% and in winter conditions to T: 10 ± 2 °C, RH: 80%.

Physiological Evaluation

We measured, manually, surface temperature and body temperature. All the samples were collected two times by condition, at 9 a m. The first data collection was made 4 d after the change of the conditions; the other one was made before the change for the next condition.

Surface temperature (sT) was measured with an IR thermometer (Pro'sKit MT-4612) in the neck and was taken very quickly, approximately 5 s per animal. Body temperature (bT) was measured in the rectal area with a digital thermometer and each measure was taken in 1 min.

Behavioral Evaluation

In this test, five video cameras and one microphone (strategically positioned inside the room) were used to monitor the behaviour of the animals, namely the lying patterns and intensity and frequency of the animals' grunts and screams, respectively.

The study of the animal behaviour with regard to their dispersion through the park was possible using video images captured 24 h/24 h and an artificial vision algorithm, specifically developed for this purpose. The algorithm works in two steps:

- *Recognition of animals and/or groups* - The algorithm looks for shapes that coincide with the contour of an animal, in this case a pig, and registers the positioning of each one in the park. If several animals are in contact forming a group of animals, the algorithm also identifies this fact.
- *Calculation of the proximity index* - Taking into account the area of the pen, the total number of animals and the position of each one, the algorithm calculates the proximity index of the animals, with results between 0–1, where 1 means that the animals are all together in a group, and zero means that the animals are as scattered as much as possible given the area of the pen.

Currently, sound and image software is still under development and will aim to detect abnormal behaviours such as animal huddle/apart and vocalizations above certain frequencies. The equipment saved, in real time, all the information in a server that could be consulted at any moment.

Productive Evaluation

We measured body weight (BW), feed intake (FI) and average daily gain (ADG) of the animals. The body weight and feed intake were measured through the individual automatic feed machine. After detecting the animals entrance, the system measured the weight and registered feed intake. At the end of each day the system calculated the average of the recorded weights, as well as the sum of the amount of feed intake.

Statistical analysis

For statistical analysis we used SAS *studio* software (v.9.4 TS1M6, 2018).

The data were analysed with *ANOVA* and multiple comparisons were taken. The statistical model was: $Y = \mu + Ei + e_{(ij)}$, where Y = parameter of interest, μ = mean, Ei = environmental conditions and $e_{(ij)}$ = residual error. The relationship between FI and ADG was analysed with non-linear regression.

Results are presented as mean ± SE and we considered significantly different at $P < 0.05$.

Results and discussion

The average temperature recorded in summer, 25.8 °C, was 2.2 °C below the lower temperature established, 28 °C. In the thermoneutrality situation, the average temperature recorded was 19.3 °C. This value was above the higher temperature of 19 °C, however, this variation was minimal, at 0.3 °C. On the other hand, in the winter situation the value obtained 17.9 °C and was 5.9 °C above the higher desired temperature, 12 °C (Table 1).

Table 1. Comparison between stipulated temperatures and average temperatures obtained in interior (Ti) and exterior (Te)

Environmental Conditions	Set Temperatures (°C)	Real Temperature (°C)	
		Ti	Te
S	30 ± 2	25.8	14.4
TN	17 ± 2	19.3	21.9
W	10 ± 2	17.9	16.8

The mean values of relative humidity recorded in summer and thermoneutrality, 60.4% and 70.8%, respectively, were 10.4 and 10.8% higher than those intended. In the winter season, this value was 3.1% higher than desired (Table 2).

Table 2. Comparison between stipulated relative humidity and average relative humidity obtained in interior (HRi) and exterior (HRe)

Environmental Conditions	Set RH (%)	Real RH (%)	
		RHi	RHe
S	50	60.4	71.3
TN	60	70.8	64
W	80	83.1	58.1

The equipment of the environmental system (heating and cooling systems) was unable to express its maximum efficiency in the different environmental situations. This happened because of the difference between the average external temperature reached and the defined internal temperature. In the summer situation, the outside temperature was 14.4 °C, which led to exhaustion of the heating system. In the winter situation, the Te was 16.8 °C, which caused major limitations in the cooling system (nebulization). Therefore, the system was unable to cool the room to the set-up temperature.

Table 3. Mean temperatures of animals, body temperature (bT) and surface temperature (sT), for the three environmental conditions

Environmental Conditions	Temperature (°C)	
	sT	bT
S	36.2 ± 0,62 [a]	38.9 ± 0,34 [a]
TN	33.6 ± 0,44 [b]	38.7 ± 0,24 [a]
W	35.2 ± 0,34 [ab]	38.4 ± 0,34 [a]
P	0.005	0.567

a, b – Values of the same column in each parameter affected by the same letter are not significantly different due to the effect of environmental conditions

We observed in Table 3 that in summer conditions sT increases significantly when compared to TN conditions ($P = 0.006$). This indicator is more variable and more influenced by the environment (Manno *et al.*, 2006). This increase in sT was also reported by Huynh *et al.* (2005), Manno *et al.* (2006) and Kiefer *et al.* (2009). These authors observed that when the ambient temperature increases, the surface temperature also increases. Surface temperature measurement is a quick and practical method of verifying that animals are outside the comfort zone (Mostaço, 2014).

As observed before, the environmental control system could not reach the set-up temperatures for W. That happened because the weather outside was too hot, this influenced the sT, so we don't observed a decrease in winter sT when compared to the TN (P=0.1).

bT, in growing and finishing pigs is about 38.8 °C (Cunningham, 1993). The results observed in this study fall within this temperature. We did not observe statistical differences between the groups when compared to TN conditions (S: $P = 0.88$; W: $P = 0.55$). Our results agree with Soerensen & Pedersen, (2015). These authors noticed that bT remains constant because of thermoregulation mechanisms. Although when the ambient temperature rises above the capacity of physiological readjustment, the retained body heat is capable of altering the state of homeothermia, this increases the rectal temperature (Huynh *et al.*, 2005; Kiefer *et al.*, 2009). The increase in bT becomes more intense with the degree of deviation of the temperature of thermal comfort, as a rule, that means that the animal is storing heat due to the failure of thermoregulation mechanisms (Ferreira, 2002, cited by Rodrigues, 2010). We do not observe this increase in our results, probably because the environmental temperatures were not too high for the animal to retain the heat.

As expected, the environmental conditions had a significant effect on the FI ($P < 0.001$) but not in the ADG ($P \geq 0.05$) (Table 4).

Regarding the FI, it was possible to observe that, in relation to thermoneutrality, it was 6% lower in the S situation and 6% higher in W. On other hand, the highest daily gain was

achieved in the TN situation, with 0.923 kg day^{-1}, and there were no significant differences between this value and those obtained in S and W simulations, 0.768 kg day^{-1} and 0.808 kg day$^{-1,}$ respectively. However, in both situations there was a decrease in the average daily gain of 17% in the summer situation and 12% in the winter situation.

Table 4. Influence of environmental conditions on growth performance of pigs

Environmental Conditions	Parameter		
	BW (kg)	FI (kg day^{-1})	ADG (kg day^{-1})
S	57.7	2.111 ^{c} ± 0.034	0.768 ^{a} ± 0.960
TN	69.9	2.473 ^{b} ± 0.030	0.923 ^{a} ± 0.086
W	86.1	2.814 ^{a} ± 0.030	0.808 ^{a} ± 0.086
P		< 0.0001	0.1036

a, b – Values of the same column in each parameter affected by the same letter are not significantly different due to the effect of environmental conditions

In S conditions, FI decreases (Quiniou, *et al.*, 2000; Pearce *et al.* 2013) as does the ADG. These results are reported by Collin *et al.* (2001), Banhazi *et al.* (2009) and Kiefer *et al.* (2009).

Due to the system failure in W conditions, the ADG is similar to the TN conditions. The FI seems to be higher in W than in TN, this cloud happened because the animals are bigger, so they eat more. During the growing period, the voluntary FI is influenced by the physiological status (age, body weight) (Kanis & Koops, 1990; cited by Quiniou *et al.*, 2000).

We verified that the correlation between FI and BW is a polynominal regression *(R^2 = 0.5723)*, represented in Figure 1. These results are in agreement with Botermans and Pierzynowski (1999). The need for dietary nutrients increases as the pigs grows, therefore, the feed intake increases with body weight (Li and Patience, 2017).

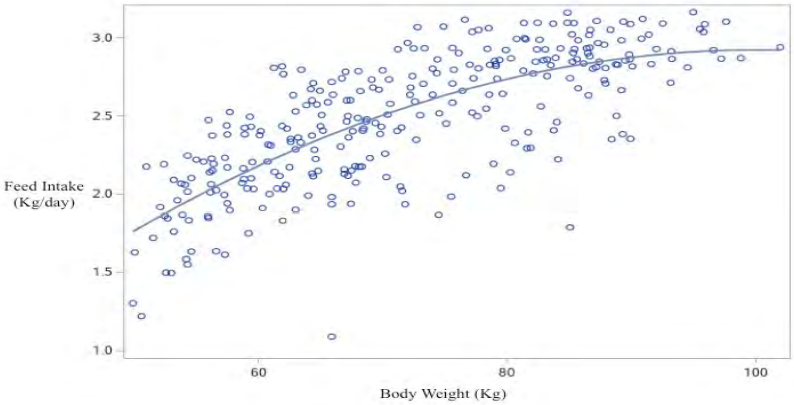

Figure 1. Relationship between FI and BW represented by a polynominal regression (R^2 = 0.5723)

At last, when the ambient temperature does not correspond to comfort levels, pigs show specific behavioural characteristics and are able to change their behaviour to adapt to the environment that surrounds them (Quiniou *et al.*, 2000). Indeed, temperature is the main parameter affecting pigs lying behaviour (Nasirahmadi *et al.*, 2015). We can observe

some of these behaviours, with the animals gathering when the ambient temperature was below the thermo neutral temperature (W condition), and spacing between them when the ambient temperature was above the thermo neutral temperature (S condition), which is in accordance with the bibliography consulted (Nasirahmadi *et al.*, 2017). Examples of the image that we recorded can be seen in Figure 2 and 3.

Figure 2. In S conditions the gilts prefer to rest apart, without contact between them

Figure 3. In W conditions the gilts choose to huddle

Conclusions

We can conclude that the welfare indicators that we used can give us information about the animal's welfare. Although we have collected some of the data manually, there are technologies that can gather and analyse the data, for example, thermo cameras that give surface temperature. Feed intake and sT changes with the environmental conditions. sT changes more that bT with the environmental conditions, so it can be more useful as a welfare indicator. We are still analysing some of the data, and have more trials to do, but we hope to collect and gather most of these welfare indicators automatically and in real time, in one platform.

In order to validate the methodology and some results, the second phase of the project (living lab) will be in a commercial farm, with a larger number of animals and it aims to test all the equipment and analyse the efficiency of the system in a real production environment.

References

Baêta, F.C. and C.F. Souza. (2010). Ambiência em Edificações Rurais: Conforto Animal. Viçosa, Mg; Brasil: UFV.

Banhazi, T.M. and Black, J.L. (2009). Livestock Farming: A suite of electronic systems to ensure the application of best practice management on livestock farms. *Australian Journal of Multi-Disciplinary Engineering*, 7(1).

Botermans, J.A.M., and Pierzynowski, S.G. (1999). Relations between body weight, feed intake, daily weight gain, and exocrine pancreatic secretion in chronically catheterized growing pigs. *Journal of Animal Science*, 77(2): 450–456.

Candiani, D., Germana Salamano, E., Doglione, L., Bruno, R., Toussaint, M., and Gruys, E. (2008). A Combination of Behavioral and Physiological Indicators for Assessing Pig Welfare on the Farm. *Journal of Applied Animal Welfare Science*, (11): 1–13.

Cruz. V.F. and Baptista, F.J. (2006). Conceitos básicos sobre ventilação no alojamento de suínos. *Revista Suinicultura,* 72: 40–48.

Cunningham, J.G. (1993). Tratado de Fisiologia Veterinária. Guanabara Koogan S.A.

Godfray, H.C.J., Beddington, J.R., Crute, I.R., Haddad, L., Lawrencwe, D., Muir, J.F., and Toulmin, C. (2010). Food Security: The Challenge of feeding Billion People. *Science*, 327: 812–818.

Huynh, T.T.T., Aarnink, J., Verstegen, M.W., Gerrits, W.J.J., Heetkamp, M.J.W., Kemp, B., and Canh, T.T. (2005). Effects of increasing temperatures on physiological changes in pigs at different relative humidities. *Journal of Animal Science*, (83): 1385–1396.

Hsia, L.C. and G.H. Lu. (1987). The effect of high environmental temperature on the protein and energy requirements of growing finishing pigs. I. The effect of dietary levels of protein and energy on the performance of pigs under ad lib feeding. *J. Chin. Soc. Anim. Sci*., 16(1-2): 1–10.

Kiefer, C., Meignen, B.C.G., Sanches, J.F., and Carrijo, A.S. (2009). Resposta de suínos em crescimento mantidos em diferentes temperaturas. *Archivos de Zootecnia*, 58(221): 55–64.

Koenders, E., Rooijakkers, L., Van Hertem, T., Vranken, E., and Berckmans, D. (2015). Towards the development of a practical visualisation tool for farmers and other stakeholders. In *Precision Livestock Farming 2015 - ECPLF 2015*, pp. 327–337.

Li, Q., and Patience, J.F. (2017). Factors involved in the regulation of feed and energy intake of pigs. *Animal Feed Science and Technology*, 233 (January), 22–33.

Manno, M.C., Oliveira, R.F.M. De, Donzele, J.L., Oliveira, W.P. De, Vaz, R.G.M.V., Silva, B.A.N., Saraiva, E.P. and Lima, K.R. de S. (2006). Efeitos da temperatura ambiente sobre o desempenho de suínos dos 30 ao 60 kg. *Revista Brasileira de Zootecnia*, 35(2): 471–477.

Mostaço, G.M. (2014). Determinação da temperatura retal e frequência respiratória de suínos em fase de creche por meio da temperatura da superfície corporal em câmara climática. MS dissertation in Engenharia de Sistemas Agrícolas. Escola Superior de Agricultura "Luiz de Queiroz", University of São Paulo, Piracicaba, Brazil.

Mota, N. (2018). A conjectura actual e a inovação na produção.

Nasirahmadi, A., Richter, U., Hensel, O., Edwards, S. and Sturm, B. (2015). Using machine vision for investigation of changes in pig group lying patterns. *Computers and Electronics in Agriculture,* 119: 184–190.

Nasirahmadi, A., Edwards, S.A., and Sturm, B. (2017). Implementation of machine vision for detecting behaviour of cattle and pigs. *Livestock Science*, 202: 25–38.

Pandorfi, H., Silva, I.D., Carvalho, J.D., and Piedade, S.M.S. (2006). Estudo do comportamento bioclimático de matrizes suínas alojadas em baias individuais e coletivas, com ênfase no bem-estar animal na fase de gestação. *Engenharia Rural*, 17(1): 1–10.

Pearce, S., Gabler, N., Ross, J.W., Escobar, J., Patience, J.F., Rhoads, R.P., and Baumgard, L.H. (2013). The effects of heat stress and plane of nutrition on metabolism in growing pigs. *Journal of Animal Science*, 91: 2108–2118.

Quiniou, N., Dubois, S., and Noblet, J. (2000). Voluntary feed intake and feeding behaviour of group-housed growing pigs are affected by ambient temperature and body. *Livestock Production Science*, 63: 245–253.

Rodrigues, N.E.B., Zangeronimo, M.G., and Fialho, E.T. (2010). Adaptações fisiológicas de suínos sob stress térmico. *Revista Eletrónica Nutritim*e, 7(110): 1197–1211.

Soerensen, D.D., and Pedersen, L.J. (2015). Infrared skin temperature measurements for monitoring health in pigs: A review. *Acta Veterinaria Scandinavica*, 57(5): 2–11.

Wathes, C.M., Kristensen, H.H., Aerts, J., and Berckmans, D. (2008). Is precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall? *Computers and Electronics in Agriculture*, 64: 2–10.

Preliminary results from a novel tail-mounted calving sensor in dairy cows

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Abstract

The objective of this study was to pilot-test a novel biosensor to predict the onset of stage two of calving in dairy cows. A monitor was developed containing an accelerometer and other gravitational measurement devices. It was attached to the upper side of the cow's tail approximately 6 cm below the anus. Three behavioural changes were monitored: (1) tail raise frequency and duration; (2) angle of tail raise; and (3) bouts of standing/lying down. Measurement of these behaviours was taken every two seconds and the data transmitted to a receiver base. The device was tested on 20 dairy cows. The time of calving was established by 24 h staff supervision and CCTV. Of the 20 cows, 12 calvings were monitored, (six primiparae, six pluriparae); five unassisted, six easily assisted and one difficult. Prolonged elevation of the tail (> 30 - 45 degrees, > 20 seconds and four repetitions within 60 minutes), either alone or in combination with an abnormal standing pattern (within a 30 minutes period) were observed within four hours of each calving (unassisted calvings two - 3.3 h; assisted calvings 45 min – 3 h). Prolonged tail elevation combined with increased restlessness was indicative of imminent calving. The monitor was able to detect and record the pattern of calving behaviours and the algorithm was able to detect distinct onset of calving-specific behavioural change up to four hours before birth.

Keywords: calving, sensor, prediction, tail, dairy cow

Introduction

The timing of calving can be difficult to predict accurately. Ideally, farmers would like to be able to predict to within a few hours when a cow is going to calve in order to observe normal calvings or to intervene during abnormal calving and to care for the newborn calf. But, both the signs of impending calving and the ability of the observer to detect and interpret them are highly variable (Lange *et al.,* 2017). Prediction of the onset of calving would potentially prevent dystocia (difficult calving) and stillbirth at unobserved calvings and facilitate prompt colostrum feeding, especially for heifer calves, and calf removal, particularly in paratuberculosis-infected herds. The primary modifiable risk factor for stillbirth in dairy cows is dystocia (difficult calving), (Mee *et al.,* 2014) and bradytocia (prolonged calving) is the most important type of dystocia in dairy heifers causing stillbirth (Mee *et al.,* 2017).

Traditionally, farmers used physiological signs of impending parturition such as udder and teat engorgement, sacrosciatic ligament relaxation, appearance of vaginal mucous, etc. to predict onset of calving. But in recent years there has been renewed interest in automated monitoring of parturition across species, primarily due to advances in technology. More than a dozen indicators of impending parturition have been tested to develop commercial calving alarms. Non-commercial approaches include monitoring blood progesterone decline, maternal heart rate and heart rate variability, feeding behaviour (eating and rumination time and frequency, dry matter intake) and detection of amniotic sac (waterbag) colour. Currently available devices predict onset of calving from body (rectal, reticuloruminal, vaginal, ear) temperature changes, abdominal contractions, tail elevation, recumbence posture, restlessness (locomotion time/bouts, standing/lying bouts), vulval separation or detection of ambient light or temperature.

Some approaches only predict the day of calving (e.g. progesterone decline precalving) while others attempt to predict the hour of calving. One area which shows potential promise is counting of tail elevations precalving as this has been shown to uniquely change within six hours of calving in cows (Miedema, 2009).

The ideal calving alarm would detect the onset of stage two of calving (when the farmer can possibly intervene) and differentiate between eutocia (normal calving) and potential dystocia.

The objective of this study was to pilot-test a new biosensor to predict the onset of stage two of calving in dairy cows. The study was also designed to detect any problems associated with *in vivo* testing of this pre-commercial prototype and to collect preliminary data from calvings to train the predictive algorithms.

Materials and methods

The prototype device consisted of a tail-mounted sensor and a base station. The activity monitor was developed for this project containing a wireless inertial unit that used an accelerometer and other gravitational measurement devices. The prototype contained a Printed Circuit Board and two rechargeable batteries within a grey waterproof casing and weighed 133 g. It was attached to the upper side of the cow's tail approximately 6 cm below the anus using a self-adhesive bandage wrap. Three behavioural changes were monitored: (1) tail raise frequency and duration; (2) angle of tail raise; and (3) bouts of standing/lying down. The accelerometer data were converted to CSV files by the algorithm within the monitor and the data were transmitted within a range of c. 10 m via radio frequency to a receiver base where they were stored on micro-SD cards. The base station was connected to the GSM network over a range of c. 30 m indoors, with a capacity for up to 20 tail units. The receiver base was connected to a laptop via the USB port. The CSV files were saved to the desktop using Microsoft Excel. The algorithm created an Excel file for each minute of recorded data. Within each file there were individual tables for each two second recording. Each table presented data in percentages of time over the previous 48 hours that the cow was either standing or lying down, and percentage of time the tail was held at various angles from 0 to > 90 degrees. In order to aggregate the data to find a pattern of behaviour, the first two second recording from each one minute Excel file was taken as representative of behaviour during that minute. For every hour, 60 of the two second recordings were combined.

The device was tested in two phases. In Phase 1, 20 dairy cows (six primiparae, 14 pluriparae) were used. Cows were housed in a group pre-calving pen and adjoining individual calving pens, both straw-bedded, at Moorepark Research Centre. Given the attachment problems detected in this study, a Phase 2 study was conducted on 10 dairy cows. The device was on the cows for between one and five days precalving. The time of calving was established by 24 h staff supervision and CCTV.

Results and discussion

Of the 20 cows, 12 calvings were monitored, (six primiparae, six pluriparae); five unassisted, six easily assisted and one difficult. The reasons for the incomplete recordings were: in the initial stages of recording, the prototype was not programmed to save background Excel files. The data were simply presented in GUI (graphical user interface) format. The GUI data could not be disaggregated enough to define trends in behavioural change (two calvings), signal was poor, resulting in data not being received by the laptop, or gaps in the data rendering it unusable (2), cows pulled the devices from each other's tails - cows in pre-calving pen dislodged the prototypes by licking and chewing in play/boredom (2), laptop in hibernation failed to record the data being sent from the monitor (1) and

antenna snapped off the receiver base (1). In recorded calvings, prolonged elevation of the tail (> 30-45 degrees for > 20 seconds and four repetitions within 60 minutes), either alone or in combination with an abnormal standing pattern (within a 30 minute period) were observed within four hours of all calvings (unassisted calvings 2 - 3.3h; assisted calvings 45 mins – 3 h).

Some practical issues arose during this study with the tail-mounted sensor. Cows dislodged some devices from each other's tails and after a period of 3 - 4 days attachment of the prototype as described caused oedema of the tail above and below the device in some cows. Hence, a follow-up study was carried out to resolve issues which arose during Phase 1. Firstly, the colour of the self-adhesive bandages and the plastic waterproof housing units were changed from blue and grey, respectively, to black. Secondly, the ProWrap bandage was replaced by a Neoprene wrap with velcro fastening. Thirdly, the sensor unit was reduced in size and weight from 133 g to 50 g. The second generation devices were attached to the tails of 10 dairy cows for up to five days before calving. These changes eliminated the problem of cows dislodging the devices and allowed the devices to remain on the tail for up to five days before oedema began to develop. Furthermore, the behavioural changes recorded in Phase 1 (tail raise frequency and duration and bouts of standing and lying down) were confirmed in the data collected during Phase 2.

Conclusions

It is concluded that prolonged tail elevation combined with increased restlessness was indicative of imminent calving. The monitor was able to detect and record the pattern of calving behaviours and the algorithm was able to detect distinct onset of calving-specific behavioural change up to four hours before birth. Thus, this prototype device shows potential to detect the onset of stage two of calving. Further study in a larger population of animals with this device is required to confirm these preliminary results.

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References

Lange, K., Fischer-Tenhagen, C. and Heuwieser, W. (2017). Predicting stage two of calving in Holstein-Friesian heifers. *Journal of Dairy Science*, 100: 4847–4856.

Mee, J.F., Sanchez-Miguel, C. and Doherty, M. (2017). Causes of stillbirth and perinatal mortality in dairy calves: A prospective, whole-herd, necropsy study. *Proceedings of the 18th International Symposium of the World Association of Veterinary Laboratory Diagnosticians,* Sorrento, Italy, p. 174.

Mee, J.F., Sanchez-Miguel, C. and Doherty, M. (2014). Influence of modifiable risk factors on the incidence of stillbirth/perinatal mortality in dairy cattle. *The Veterinary Journal*, 199: 19–23.

Miedema, H. (2009). Investigating the use of behavioural accelerometer and heart rate measurements to predict calving in dairy cows. Doctoral Dissertation, University of Edinburgh, UK.

Innovative method for early detection followed by chemical characterisation of pregnancy in grazing beef cows

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Abstract

The extensive nature of grazing systems creates data gaps concerning cows' physiological status, especially where natural service is the breeding strategy. The lack of online information hinders informed decision-making regarding individual treatment, feed additives, pasture management, etc. Early pregnancy detection addresses all these and provides unique information concerning early embryonic death occurrence. In this study we analysed volatile organic compounds emitted from cows' urine in order to characterise pregnancy, using an innovative «Scent recorder» (NanoScent, Israel, ltd.). Twenty grazing beef cows were palpated for pregnancy and urine samples were collected. The gas phase over each sample was pumped through the sensor, resulting in absorption of molecules to an array of gold nano-sensors each covered with specific ligand. Feature extraction from the sensors was processed according to a protocol developed in the Technion nano-chemistry lab, Israel. Three features derived from different sensors showed significant differences between pregnant and open cows ($P < 0.05$), 13 features which showed differences with P values < 0.09 were considered sub-significant. Statistical analysis was performed using SAS-JMP applying Wilcoxon-Kruskal test. Applying model using two features resulted in 95% accuracy, with only one cow misclassified (false positive). Palpation resulted in 90% accuracy, misclassifying two cows (false negative). Conception date (determined by pedometric system) showed pregnancy detection by the «Scent recorder» as early as 10 + 2 days. Analysis of the urine volatiles was performed by GC-MS. Analysis discovered molecules, known in different physiological and chemical contexts. Their possible role in pregnancy needs to be further researched.

Keywords: electronic nose, nano sensors, volatile organic compounds, pregnancy detection.

Introduction

Cause and consequence gaps are inherent in extensive grazing beef cattle systems. Lack of online information concerning cows' physiological and reproductive status hinders informed decision-making regarding individual and herd treatment, feed additives, pasture management, and so on. Furthermore, with the common use of natural service (breeding bulls) there is no data concerning conceptions and consequently calving dates. Calving events and the following 24 hours are the most sensitive period in the whole production cycle and bear with it the highest loss rate, starting with dystocia, followed by low vitality of the newborn calf, insufficient colostrum suckling and more. An early and precise pregnancy diagnosis addresses all these and provides unique information concerning early embryonic death occurrence. In dairy farms, early identification of nonpregnant cows post insemination can improve reproductive efficiency and pregnancy rate by decreasing the interval between AI services and increasing AI service rate.

Currently different methods (direct and indirect) are in use for diagnosis of pregnancy. The direct methods include rectal palpation and ultrasonography. However, their application is limited in terms of accurate detection by day 35 and 28 post breeding respectively. Additionally, they are costly and invasive and the expertise of a veterinarian is required. Indirect methods include immunological based assay for detection and quantitation

of target proteins (Pregnancy Associated Glycoprotein: PAG) and hormones such as progesterone (P4), pregnadiol, interferon tau related to pregnancy (Vandaele *et al.*, 2005). These methods have inherent limitations of specificity and false positive results in ELISA. Furthermore, they also require invasive collection of body tissues and they are costly and time consuming. To date, early and precise pregnancy detection in bovine is unfeasible.

An emerging diagnostic approach for infectious disease at its earliest stages relies on volatile organic compounds (VOCs) that are emitted from the infectious agent and/or the host. The successful analysis of infectious disease-related VOCs is based on principles of cell biology. In disease formation, both host and invading cells can undergo structural changes, one example of which would be oxidative stress, i.e. a peroxidation of the cell membrane that causes VOCs to be emitted (Kneepkens *et al.*, 1994). What is particularly significant about this approach is that each type of disease has its own unique pattern of VOCs; therefore, the presence of one disease would not mask other disease types (Dummer *et al.*, 2011). These VOCs can be detected directly from: 1) cultured cells, 2) urine (i.e. the mixture of VOCs trapped above the cells, or above the urine in a sealed vessel) (Naraghi *et al.*, 2010); or 3) exhaled breath (Lechner & Rieder, 2007).

Reactive oxygen species (ROS) are generated as by-products of aerobic respiration and metabolism. Mammalian cells have evolved a variety of enzymatic mechanisms to control ROS production, one of the central elements in signal transduction pathways involved in cell proliferation, differentiation and apoptosis. ROS and antioxidants have been implicated in the regulation of reproductive processes in both animal and human, such as cyclic luteal and endometrial changes, follicular development, ovulation, fertilization, embryogenesis, embryonic implantation, and placental differentiation and growth (Al-Guborya *et al.*, 2010). High levels of ROS during embryonic, fetal and placental development are a feature of pregnancy. Rueda *et al.* (1995), discovered significantly higher levels of mRNA encoding catalase, an enzyme responsible for detoxification of superoxide to water, in *Corpus Luteum* (CL) collected from 21 days pregnant cows compared to CL collected from cows in day 21 of estrous cycle (functioning compared to regressed CL). This implies that a decline in expression of specific oxidative response genes during luteolysis, and maintained expression of these genes in the CL during pregnancy, may prevent oxidative damage. In other words, inherent ROS level increase in pregnancy is dealt by indirect pathways. This evidence led us to hypothesize that we can apply VOC's analysis to differentiate between pregnant and non-pregnant cows. In this paper we describe a field trial performed in order to test the feasibility of early pregnancy detection using an innovative device containing an array of sensors, termed Nano Artificial NOSE (Peled *et al.*, 2012; Hakim *et al.*, 2011; Tisch & Haick, 2010). Unlike gas chromatography and mass spectrometry, electronic noses cannot chemically characterise or directly quantify individual molecular components, but are able to separate and recognise different gas mixtures by 'fingerprinting'. This unspecific sensor approach is analogue to the mammalian olfactory system (Buck & Axel 1991), and is similarly specific since each smell has a unique fingerprint. In this study we performed GC-MS analysis following the dichotomic detection of pregnancy by the artificial nose in order to detect changes in concentrations of specific molecules in the urine of pregnant compared to non-pregnant cows. Some possible explanations regarding these changes and their possible role in supporting pregnancy establishment and maintenance are offered in the discussion.

Objectives

- Test the feasibility of an early pregnancy detection using an innovative device termed Nano Artificial NOSE.
- Characterise chemical compounds and their concentration change between pregnant and non-pregnant beef cows.

Materials and methods

Animals

Urine was collected from 20 healthy beef cows grazing on pasture near Kibbutz Snir, Northern Galilee, Israel. The cows were randomly selected out of a herd of 120 cows. Breed composition was Simmental crosses, typical to any commercial herd in Israel. The ages of the cows ranged between four to 13 years at the time of the study. All the cows were born at the farm and had good production records (yearly calvings). The cows were nursing calves between the ages of two to six months. The experiment was performed on 25 April 2017, (spring time) when vegetation's biomass and nutritional value just passed its peak. Pasture vegetation biomass averaged 6,000 kg ha^{-1} with 35% dry matter content and 14% protein. Cows were brought to kennel the same day to be pregnancy checked by an experienced veterinarian who performed rectal palpation. Urine was collected following each check.

The breeding season started on 10/1/17 when bulls were introduced into the cows' herd. Breeding season ended on 23/4/17 two days prior to the trial day. Resulting calving season occurred between October 2017 and February 2018. All cows that were detected as pregnant calved during this season. Cows that were detected as non-pregnant both by the E-Nose and by the veterinarian didn't calf during this season. Two cows that were detected as non-pregnant by the veterinarian and pregnant by the E-Nose, calved on the end of the season, indicating a very early pregnancy detection by the E-Nose.

Electronic Nose

The electronic nose, is an array of 18 chemiresistive films of gold nanoparticle (GNP) sensors, each covered with a different chemical absorber, the organic functionalities of which provided broadly cross-selective absorption sites for VOCs. The gold particles provide the electric conductivity and the organic film component provides sites for the sorption of analyte (guest) molecules. Details of the sensing materials synthesis have been described elsewhere (Peled *et al.*, 2012; Tisch & Haick, 2010). Sensors output was monitored for a change in resistance using a custom program (LabView, National Instruments). All sensors were monitored simultaneously through an Agilent 34980A multifunction switch. The general setup allowed for measuring normalised changes of conductance as small as 0.01%, corresponding to chemical concentration changes of several ppb. The system was degassed under vacuum for five minutes between each two consecutive samples.

We used the original version of the device in this trial, located on the Technion's nano-chemistry laboratory. A smaller, hand-held version currently manufactured by «NanoScent» ltd. is operative and suitable for field conditions. The device is shown in the following pictures:

Picture 1. NanoScent hand held electronic nose. On the right: the chamber, on the left: the sensors inside the chamber. Dimensions of the chamber: height:15 cm; depth: 17 cm; width: 8 cm.

Sample collection and analytical procedure

Urine samples were collected on field by manual stimulation of the perineal region into plastic containers and were immediately transferred into cell culture flasks (75 cm), sealed and kept in a picnic cooler, then transferred to the Technion, Haifa and kept in a refrigerator until the following day. The headspace of each urine sample (mixture of VOC's trapped above the urine in the glass vessels) was analysed the next day, by GC-MS and by the E-Nose.

GC-MS analysis: was performed employing a Gas Chromatography–Mass Spectrometry equipment (GC–MS-QP2010; Shimadzu Corporation, Japan), combined with a thermal desorption system (TD20; Shimadzu Corporation, Japan). The molecular structures of the VOCs were determined by spectral library matching, using the Automated Mass Spectral Deconvolution and Identification System software.

Data analysis

The GC-MS results for a given identified compound were compared across two groups: pregnant and non-pregnant, using SAS JMP software applying Wilcoxon-Kruskal test at a significance level of p-value < 0.05.

The electronic nose sensors responses, defined as the relative resistance change experienced by the sensors immediately after exposure to the head-space of the urine sample, were processed using feature extraction UI developed in the Technion lab (MATLAB based). The features included: area under curve (AUC), delta R peak, mid and end (change in the sensor resistivity relative to its vacuum response at the peak, middle and end of response). The features were used as inputs for Discriminant Factor Analysis (DFA) pattern recognition algorithm (Ionescu *et al.*, 2002).

Results and discussion

Calving dates

Pregnancy test results were compared with pedometric data recorded by a long range pedometric system operating automatically in the pasture. None of the cows appearing in Table 1 showed estrus cycles following the 25/4/17 (test day). Calving dates of the cows that were detected as pregnant by the E-Nose are presented in Table 1. Two cows detected by the E-Nose were not detected by the rectal palpation conducted by an experienced veterinarian. These cows apparently conceived few days prior the test day, as validated by the following calving dates. Cows that were non-pregnant according to the E-Nose and the veterinarian showed estrus cycles in the pedometric system and didn't calf during the following calving season.

Table 1. Calving dates of the study cows

Cow	E-Nose test	Palpation test	Calving date
580	Yes	No	24/1/18
1389	Yes	No	7/1/18
4284	Yes	Yes	21/12/17
14101	Yes	Yes	16/11/17
4054	Yes	Yes	1/11/17
1419	Yes	Yes	20/10/17
7087	Yes	Yes	27/10/17

The rest of the cows that were tested as negative both by palpation and by E-Nose, didn't calf during the relevant calving season

Analysis of urine samples with the electronic nose

Each urine sample was processed as described and the head-space was vacuum pumped through the electronic nose. Features extraction resulted in three features showing significant differences ($P < 0.05$) and 13 features showing differences with (p values < 0.09). Table 1 presents the three features showing significant differences.

Table 2. Single sensor/feature results for pregnant and non-pregnant cows. Values expressed in Ohms (O)

Features	P-value	Average pregnant	Average non-pregnant
S22 dRend	0.0325	3.70 ± 0.23	4.27 ± 0.62
S39 dRmid	0.0495	1.11 ± 0.43	1.76 ± 0.62
S19 dRpeak	0.0129	1.41 ± 0.127	1.62 ± 0.19

All features shown in the table expressed a decline in pregnant compared to non-pregnant cows' samples. This fact may suggest a decline in absorption of VOCs to the sensors for the pregnant cows, resulting in a 'thinner' cover layer, causing smaller resistivity change. Another possible explanation may be a change in the absorbed (guest) VOCs' electric charge. The significant differences between pregnant and non-pregnant samples are expressed in different stages of each sensor response. In S22 the significant change occurs at the end of the sensor's response, S39 in the middle and S19 in the peak.

DFA analysis was then performed, applying the palpation pregnancy results as determined by the veterinarian for the 'yes' and 'no' groups (pregnant and not pregnant, respectively). The DFA plot obtained employing two features (S30 dRmid and S19 dRpeak) is shown in Figure 1. The horizontal line represents the division according to the DFA model, the dots above the line represent non-pregnant cows and the dots under the line represent pregnant cows according to the sensor's diagnosis. The two cows identified as pregnant by the model and non-pregnant by the veterinarian, calved 274 and 282 days following the sampling day, meaning a 100% accuracy achieved by DFA analysis and an extremely sensitive technology of 100% sensitivity of the electronic nose. However, pregnancy shorter than 282 days is possible (though not likely), and the cow could have conceived a few days post sampling day. Therefore, we assume a possible misclassification of one cow by the model, and an accuracy of 95% detection by the electronic nose. Whether or not there was one misclassification, this is the first record of pregnancy detection at such an early stage of either few or ten days approximately, known to us.

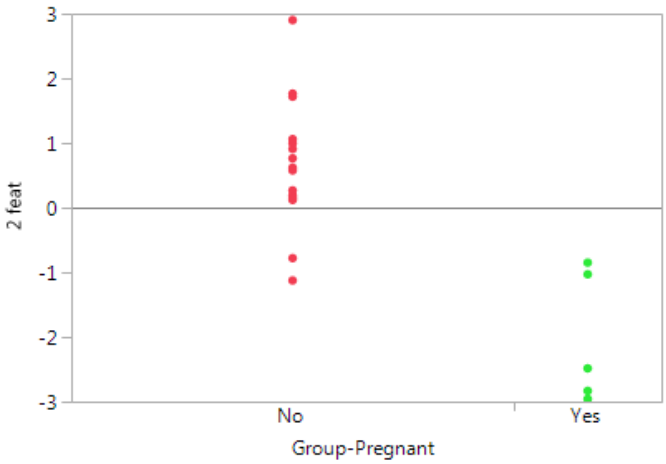

Figure 1. DFA analysis using two features. Black dots represent non-pregnant, grey dots represent pregnant cows according to palpation check, horizontal line divides non-pregnant (above) and pregnant (under) according to the model

Chemical analysis

CG-MS analysis resulted in a significant difference in one molecule between pregnant and non-pregnant cows (p = 0.02) and five other molecules with *p* values around 0.06 which needed consideration in our opinion. The results are presented in Table 2.

Table 3. Molecules detected by GC-MS and their *p* values. Values expressed in ppb

Molecule	P-value	Least square mean ± SE pregnant	Least square mean ± SE non-pregnant
Tridecane, 4-methyl	0.0265	3,000 ± 1,000	733 ± 175
Benzen	0.05	54,076 ± 26,574	20,570 ± 7,901
Ethanol	0.067	287,718 ± 226,490	55,006 ± 25,453
4-Heptenal, (Z)	0.063	88.75 ± 89.9	456.1 ± 144
1-Octene-3-one	0.065	1,302 ± 690	542 ± 245
Pinocarvone	0.067	3,745.25 ± 1,195	2,069.45 ± 1,104

Tridecane 4-methyl is a non-cyclic alkane with an anti-androgenic activity, patented in 2006 as a chemotherapeutic drug for treatment of prostate gland cancer in humans (US7018993). Its increased level during pregnancy might imply a support to the *corpus luteum* progesterone secreting activity by depressing estrogen levels. This finding is intriguing considering its implication of existence of pregnancy supporting mechanisms unknown to date, acting in a completely different arena of non-protein, small molecules. We had difficulty explaining possible advantages in Benzene and Ethanol level elevations in pregnant cows. It could be an expression of the reduced antioxidative activity known to occur during pregnancy (Al-Guborya *et al.*, 2010). 4-Hepenal is an alkene found in milk. It was patented as prophylactic and therapeutic agent for cancer treatment (US2012196864), as an agent for treatment of metabolic disease and skin disease (US2008234229; US7589239)

in humans. It is also an antagonist to reductase activity. The decrease in 4-Hepenal level during pregnancy probably contributes to reducing oxidative damage by reducing its anti-reductase activity. On the other hand, it might reduce the possibly favorable effect of its antimicrobial activity. This implies the complexity of the discovered chemistry and its interpretation. 1-Octene-3-one is a degradative reduction product of skin lipid peroxides with Fe^{+2}. Its reaction with CO_2 attracts several species of mosquitos (Takken & Kline, 1989). Behar, 2018 (personal communications) found that 1-Octene-3-one increased horses' susceptibility to infection by SIMBU group viruses. 95% of the cows in the study herd are positive to SIMBU viruses as indicated by levels of antibodies in sera sampled in the last two years. The role of these viruses in the increased abortion rates observed in this herd is being studied presently. Application of environmental management to reduce presence of these viruses' vectors is also being tested presently. Pinocarvone (2(10)-pinen-3-one) possesses anti-microbial and anti-fungicidal activity. It is commercially produced from Tasmanian Blue Gum (*Eucalyptus globulus*) to ease skin irritations in humans. The increased level of pinocarvone might be connected to the increased level of 1-Octene-3-one since each produces an opposite effect.

Conclusions

This paper proposed a new nano technology for early pregnancy detection based on identifying unique VOCs, or profiling VOCs specific to pregnancy in cows' urine. The electronic nose used in this study showed great promise as an accurate, fast, non-invasive tool applicable in farm conditions. The earliest pregnancies detected were a few days old, possibly revealing VOCs characteristic to pregnancy establishment that are unfamiliar as such to-date. These VOCs need to be further researched. Their chemical structures and activities suggest pathways aimed to decrease oxidative damage inherent in pregnancy, and they might bear a potential for pregnancy supporting protocols. Furthermore, the possibility to detect pregnancy at such an early stage, may provide important information concerning early embryonic deaths, and possibly even embryogenesis and embryo implantation. These data are unavailable to-date, hindering treatment in a crucial stage of production.

References

Al-Guborya, K.H., Fowler, P.A. and Garrel, C. (2010). The roles of cellular reactive oxygen species, oxidative stress and antioxidants in pregnancy outcomes. The International *Journal of Biochemistry & Cell Biology*, 42: 1634–1650.

Buck, L. and Axel, R. (1991). A novel multigene family may encode odorant receptors: A molecular basis for odor recognition. *Cell*, 65: 175–187.

Dovgolevsky, E. Konvalina, G., Tisch, U. and Haick, H. (2010). Monolayer-capped cubicplatinum nanoparticles for sensing nonpolar analytes in highly humid atmospheres, *Journal of Physical Chemistry*, C 114: 14042–14049.

Dovgolevsky, E., Tisch, U. and Haick, H. (2009). Chemically sensitive resistors based on monolayer-capped cubic nanoparticles: towards configurable nanoporous sensors, Small 5: 1158–1161.

Dummer, J., Storer, M., Swanney, M., McEwan, M., Scott-Thomas, A., Bhandari, S., Chambers, S., Dweik, R. and Epton, M. (2011). Analysis of biogenic volatile organic compounds in human health and disease. *Trends in Analytical Chemistry,* 30: 960–967.

Hakim, M., Billan, S., Tisch, U., Peng, G., Dvrokind, I., Abdah-Bortnyak, R., Kuten, A. and Haick, H. (2011). Diagnosis of head-and-neck-cancer from exhaled breath, British Journal of Cancer, 104: 1649–1655.

Ionescu, R., Llobet, E., Vilanova, X., Brezmes, J., Sueiras, J.E., Caldererc, J. and Correig, X. (2002). Quantitative analysis of NO_2 in the presence of CO using a single tungsten oxide semiconductor sensor and dynamic signal processing. *Analyst*, 127: 1237–1246.

Kneepkens, C.M.F., Lepage, G. and Roy, C.C. (1994). The potential of the hydrocarbon breath test as a

measure of lipid peroxidation. *Free Radical Biology and Medicine*, 17: 127–160.

Lechner, M. and Rieder, J. (2007). Mass spectrometric profiling of low-molecular-weight volatile compounds – diagnostic potential and latest applications. *Current Medicinal Chemistry,* 14: 987–995.

McDonald, J.H. (2009). Wilcoxon signed-rank test. In: McDonald, J.H. Handbook of Biological Statistics, Sparky House Publishing, Baltimore, MD, USA, 186–190.

Naraghi, K., Sahgal, N., Adriaans, B., Barr, H. and Magan, N. (2010). Use of volatile fingerprints for rapid screening of antifungal agents for efficacy against dermatophyte Trichophyton species. *Sensors and Actuators B*, 46: 521–526.

Peled, N., Ionescu, R., Nol, P., Barash, O., McCollum, M., VerCauteren, K., Koslowa, M., Stahl, R., Rhyan, J. and Haick, H. (2012). Detection of volatile organic compounds in cattle naturally infected with Mycobacterium bovis. Sensors and Actuators B 171– 172, 588– 594.

Peng, G., Hakim, M., Broza, Y., Billan, S., Abdah-Bortnyak, R., Kuten, A., Tisch, U. and Haick, H. (2010). Detection of lung, breast, colorectal, and prostate cancers from exhaled breath using a single array of nanosensors, *British Journal of Cancer*, 103: 542–551.

Peng, G., Tisch, U., Adams, O., Hakim, M., Shehada, N., Broza, Y.Y., Billan, S., Abdah-Bortnyak, R., Kuten, A. and Haick, H. (2009). Diagnosing lung cancer in exhaled breath using gold nanoparticles. *Nature Nanotechnology*, 4: 669–673.

Rueda, B.R., Tilly, K.I., Hansen, T.R., Hoyer, P.B. and Tilly, J.L. (1995). Expression of superoxide dismutase, catalase and glutathione peroxidase in the bovine corpus luteum: evidence supporting a role for oxidative stress in luteolysis. *Endocrine*, 3: 227–232.

Takken, W. and Kline, D.L. (1989). Carbon dioxide and 1-octen-3-ol as mosquito attractants. *Journal of the American Mosquito Control Association*, 5(3): 311–316.

Tisch, U. and Haick, H. (2011). Arrays of chemisensitive monolayer-capped metallic nanoparticles for diagnostic breath testing, *Reviews in Chemical Engineering*, 26: 171–179.

Tisch, U. and Haick, H. (2010). Nanomaterials for cross-reactive sensor arrays, MRS Bulletin 35: 797–803.

Vandaele, L., Verberckmoes, S., El Amiri, B., Sulon, J., Duchateau, L., Van Soom, A., Beckers, J.F. and de Kruif, A. (2005). Use of homologous radioimmunoassay (RIA) to evaluate the effect of maternal and foetal parameters on pregnancy associated glycoprotein (PAG) concentrations in sheep. *Theriogenology,* 63: 1914–24.

Application of near infrared reflectance spectroscopy for mineral analysis in hay

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Abstract

The use of near infrared reflectance spectroscopy (NIRS) was explored to predict macro and micro mineral concentrations in hay samples. Hay samples (n = 37) from different locations in Ireland representing a wide distribution of grass species, season, time of harvest and soil types were used to examine the impact of sample preparation and presentation procedures (presence of residual moisture (RM) and particle size (PS) variation i.e. 0.5 and 1 mm) on resultant NIRS calibration and prediction statistics. The samples were scanned in reflectance mode using NIRS DS2500 (1,100 – 2,500 nm) and analysed for Ca, P, Mg, S, Na, Mn, Fe, Cu and Zn using inductively coupled plasma mass spectrometer (ICP - MS) for computation of reference data. Calibration models (n = 24) were developed using modified partial least squares regression (MPLS) based on cross-validation and tested using a validation set (n = 13). To optimise calibration accuracy, mathematical treatments (first and second derivatives) of the spectra and scatter corrections (SNV and Detrend) were applied. Better calibration statistics were obtained at 0.5 mm particle size without re-drying samples for Mg, S, Na, P and Fe. However, calibrations for Mn and Cu performed better at 0.5 mm with re-drying. The predictability of each mineral seems to be more affected by particle size than residual moisture. Overall, these results showed that NIRS prediction accuracy for different minerals vary with the sample preparation and presentation procedure.

Keywords: NIRS, mineral analysis, particle size, residual moisture

Introduction

Minerals are essential in horse nutrition as they play vital roles such as formation of structural components, enzymatic cofactors, energy transfer, and as integral parts of vitamins, hormones and amino acids (Nutrient Requirement of Domestic Animals, 2007). The horse obtains most of its required minerals from pasture, roughage, grains and mineral supplements. It is essential to know the mineral composition of these forages. However, chemical reference methods for the determination of mineral components are laborious and time consuming (De Boever *et al.*, 1995).

Near-infrared reflectance spectroscopy (NIRS) is widely accepted as a good tool for the analysis of several chemical constituents in different tissues of plant species. The technique is extremely rapid, non-destructive, involves no sample preparation, and is less expensive than conventional methods (Pestico *et al.,* 2008). It is based on selective absorption of electromagnetic radiation from 800–2,500 nm in accordance with the characteristic vibration frequencies of functional groups (De Boever *et al.,* 1995). Components measured include total N, moisture, fibre, starch, individual sugars, amino acids and plant tannins (Foley *et al.,* 1998).

The use of NIRS for the analysis of elements in forages was first reported by Shenk *et al.* (1981). NIRS has been used to determine macro and micro elements in a wide range of agricultural products and foods (McClure, 2003). However, these have produced contrasting results with low accuracy and precision. This could be attributed to the absence of absorption bands for minerals in the near-infrared region (Shenk *et al.,* 1992). Moreover, it is not clear which mineral element can be determined using this technique.

The determination of minerals by NIRS is generally dependent on the occurrence of those minerals in organic or hydrated molecules (Clark *et al.,* 1987; Vazquez de Aldana *et al.,* 1995). Also, mineral determination varies among species, or mineral percentages may simply be correlated to some organic material that the NIRS can easily measure.

The determination of the nutritional composition of feed and forage samples using NIRS is based on developed calibration models. This involves the derivation of a mathematical relationship between reference values obtained with a standard method and the spectral data. This information should be gleaned for many samples and should be representative of the normal sample variation (De Boever *et al.,* 1995). The accuracy of NIRS calibration models can be altered due to changes in sample moisture content (Baker *et al.,* 1994; Dardenne *et al.,* 1995). Consequently, lengthy procedures such as the spectral meaning of scans (De Boever *et al.,* 1997), the removal of residual moisture (RM) through additional oven drying (Givens *et al.,* 1991) and the creation of repeatability files (Baker *et al.,* 1994; Dardenne *et al.,* 1995) have been developed. In addition, particle size (PS) variation has been reported to account for up to 90% of the variation in the spectral profile (Baker and Barnes, 1990). In a study by Lovett *et al.* (2005), it was observed that particle comminution consistently improved prediction accuracy as samples ground to pass a 1 mm screen provided the lowest standard error of cross validation (SEC) and/or standard error cross-validation (SECV) statistics with most parameters investigated. Hence, the right sample preparation and presentation method for the achievement of accurate and reliable mineral analysis is critical.

Therefore, the objectives of this study were to determine the effect of variation in particle size and the presence of residual moisture for optimum sample preparation and presentation on calibration models and improvement of predictive accuracy for mineral analysis using the NIRS.

Materials and methods

Sample description and preparation

A population of hay samples (n = 37) representative of those fed to horses from different locations in Ireland was used for this study. Locations varied in soil characteristics (texture, organic matter, N content, pH) and farm management with the primary aim to maximise variability of the samples. The samples were dried at 105 °C in a fan oven to a constant weight, ground through a 0.5 and 1.0 mm screen in a Cyclotec mill and stored in polyethylene containers.

Examination of the effect of particle comminution (milled through a 0.5- or 1.0- mm screen) and sample residual moisture content on NIRS spectra resulted in four treatment combinations. Initially, samples were passed through a 1 mm screen using a Cyclotec mill (FOSS) and subsequently scanned. The same sample was then passed through a 0.5 mm screen and scanned. At each stage, the samples were scanned with or without the presence of residual moisture. The removal of the residual moisture was achieved by an additional oven drying for one hour at the original oven temperature (105 °C) and then cooled in the desiccator.

Reference data acquisition

About 0.5 g portion of ground sample was digested with 10 mL of concentrated nitric acid in an open vessel using a digiblock digester (Labtech, ED36S model). Samples were cooled to room temperature, filtered and made up to 100 mL with deionised water. The samples were stored at 4 °C until analysis. The samples were analysed for Ca, P, Mg, S, Na, Mn, Fe, Cu and Zn in duplicate using the ICP-MS for computation of reference data.

NIRS acquisition of spectra data

Ground and dried forage samples were placed in a 50 mm diameter ring cup and scanned in reflectance mode at 4 nm intervals from 1,100–2,500 nm using a DS2500 Foss NIRS system. WinISI 4.0 software was used for spectral data collection, spectral processing and calibration development. Reflectance data were stored as the logarithm of reciprocal of reflectance (1/R). The samples were subsequently divided into calibration (n = 24) and validation (n = 13) sets.

Statistical Analysis

Calibrations were performed by modified partial least squares regression (MPLS). To optimise the accuracy of calibration, several scattering corrections and mathematical treatments were tested (standard normal variate, (SNV); De-trending, (DT); first derivative and second derivative). Assessment of the calibration model was performed by cross-validation. This was applied to avoid overfitting. During cross-validation, the calibration set was divided into five groups, using one group to check the results and the other four to construct the calibration model. Samples with high prediction residuals values, which were more than 2.5 times SECV were eliminated. The best calibration model was selected for each mineral based on the lowest SEC, SECV and highest 1-variance ratio (1-VR) (Stone, 1974).

After the development of calibration models, the models were subjected to external validation by application to a validation set. Spectra were recorded seven times and the spectral average was taken. The predicted values were compared with the laboratory results obtained. The prediction capacity of the model was assessed using the ratio performance deviation (RPD) parameter, defined as the relationship between the standard deviation (SD) of the chemical method for the collation of the reference data and that of the standard error of prediction (SEP) of the NIRS model (Chang *et al.*, 2001). Three categories of RPD values have been reported: category A with a SD/SEP > 2.0 for good models, category B with SD/SEP between 1.4–2.0 for models that could be improved using different calibration strategies, and category C with SD/SEP < 1.4 for models that may not be reliable for prediction using NIRS (Chang *et al.*, 2001).

Results and discussion

Mineral composition of hay

The statistical data for the population sets used in calibration and validation processes for both macro-minerals and micro-minerals analysed are presented in Table 1. The samples analysed varied considerably in mineral composition as shown by the range and CV. This is possibly as a result of the variation in soil types, fertilizer management and location. For the macro-minerals, the coefficient of variation (CV) was similar for all the minerals except for Na (54.27%). The wide variability obtained in Na concentration was also reported by Clark *et al.* (1987) within a single species and by Vazquez de Aldana *et al.* (2008) in a mixed grass species. The high variability in Na concentrations could be attributable to differences in Na translocation to different plant structures. While there tend to be very little Na translocation to storage and reproductive structures via phloem transport, most of the Na translocation is towards the vegetative structure via xylem transport (Subbarao *et al.*, 2003). Coefficient of variation for Mn and Fe (82.50–95.44%), respectively, were the highest for the micro-minerals. The variability in elemental composition was considered suitable for developing NIRS calibrations for these elements.

Table 1. Statistical summary of the macro and micro mineral composition of samples for calibration and validation. standard deviation (SD); coefficient of variation (CV)

Mineral	Mean	Range	SD	CV (%)
Macro-mineral (g kg^{-1} DM)				
Ca	4.17	2.54 – 6.26	1.099	24.45
P	2.09	0.99 – 3.24	0.521	24.94
Mg	1.26	0.62 – 1.72	0.313	24.70
S	1.37	0.77 – 1.76	0.289	21.21
Na	1.82	0.20 – 4.60	0.990	54.27
Micro-mineral (mg kg^{-1} DM)				
Mn	135.33	28.70 – 483.00	111.640	82.50
Fe	74.53	31.30 – 220.30	71.122	95.44
Cu	3.79	2.00 – 6.00	1.056	27.91
Zn	19.31	11.00 – 33.70	4.821	24.97

NIRS calibration statistics

Table 2 shows the calibration equations selected from the four treatment combinations resulting in the best statistics for the prediction of each of the minerals in hay samples. For the macro-nutrients, sample combinations of 0.5 mm and dried, resulted in the best calibration statistics for P, Mg, S, and Na. This could be attributed to less spectral noise caused by particle size and moisture band disturbance. Similar to the trend observed in the calibration statistics for macro-minerals, sample combinations consisting of lower particle size (0.5mm) resulted in better calibration models for Mn, Fe and Cu; however, the effect of moisture contents varied.

The R^2 for macro and micro minerals are within the range of 0.83–0.95 and 0.93–0.95, respectively, similar to the R^2 reported by Vazquez de Aldana *et al.* (2008) and Ruano Ramos *et al.* (1999). The R^2 may not be a suitable indicator of evaluating NIRS models of minerals because NIRS is not directly measuring the minerals (Huang *et al.*, 2009). This is noticeable from the increased variation ratio of Fe (based on 1-VR value of 0.33) but with a high R^2 of 0.9517.

NIRS validation statistics

As previously stated, the best calibration model from the four sample combinations were selected for each of the minerals. It was expected that the selected calibration models generate the most accurate and reliable validation statistics, however, this was not the case. It was observed that calibration equations that were less statistically reliable resulted in better prediction when tested on the validation set for all the minerals except for S and Mn. This could possibly be attributed to the need for the expansion of the sample population set for calibration and validation to increase variability as this was an exploratory study utilizing small population size.

Table 2. Calibration statistics for measurement of minerals in hay samples. particle size in mm and residual moisture (PS (mm) + RM), coefficient of determination (R^2), standard error of calibration (SEC), standard error of cross-validation (SECV); 1-variance ratio (1-VR)

Mineral	PS (mm) +RM	SEC	R^2	SECV	1-VR
Macro-mineral (g kg^{-1} DM)					
Ca	1.0 dried	0.233	0.9522	0.627	0.6385
P	0.5 dried	0.148	0.9005	0.276	0.6370
Mg	0.5 dried	0.069	0.9583	0.189	0.6769
S	0.5 dried	0.115	0.8647	0.116	0.8545
Na	0.5 dried	0.457	0.8325	0.799	0.4662
Micro-mineral (mg kg^{-1} DM)					
Mn	0.5 re-dried	30.597	0.9308	54.946	0.7662
Fe	0.5 dried	2.8922	0.9517	10.2507	0.3662
Cu	0.5 re-dried	0.2969	0.9331	0.6304	0.6856
Zn	1.0 re-dried	1.2939	0.9494	3.7472	0.5532

Table 3. Validation statistics of for NIRS prediction of minerals in hay samples. Particle size and residual moisture (PS (mm)+RM), coefficient of determination (R^2), standard error of prediction (SEP), 1-variance ratio (1-VR), ratio performance deviation (RPD = SD/SEP)

Mineral	PS (mm) +RM	R^2	SEP	Bias	RPD
Macro-mineral (g kg^{-1} DM)					
Ca	0.5 re-dried	0.393	0.9	-0.35	1.244
P	1.0 dried	0.813	0.18	0.11	1.722
Mg	0.5 re-dried	0.348	0.20	0.0	1.25
S	0.5 dried	0.169	0.25	-0.01	1.12
Na	0.5 re-dried	0.222	0.55	0.09	1.127
Micro-mineral (mg kg^{-1} DM)					
Mn	0.5 re-dried	0.346	86.709	27.947	1.206
Fe	1.0 dried	0.001	61.573	17.549	0.979
Cu	1.0 dried	0.547	0.491	-0.161	1.473
Zn	1.0 dried	0.550	3.075	0.282	1.413

Table 3 shows the details of the validation statistics for the best prediction of macro and micro minerals in hay. The RPD was consistently lower than 2 for all the minerals analysed. P, Cu and Zn had RPD values within the range of 1.4 - 2.0 suggesting models could be improved through different strategies. Even though RPD values of < 1.4 signify statistics with poor reliability (Ca, Mg, S, Mn and Na), further study is ongoing with larger population set to verify this by increasing the sample population size for the calibration and validation sets.

Conclusion

Smaller particle size (0.5 mm) and sample presentation without re-drying improved the calibration statistics of NIRS for macro-minerals, except for Ca. Accuracy of NIRS calibration and predictive models are altered due to changes in sample moisture and particle size. Overall, our study has shown that NIRS has potential to accurately quantify some minerals in hay. Further studies are ongoing to establish the best sample preparation and presentation for mineral analysis.

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References

Baker, C.W., Barnes, R.J. (1990). The application of near infrared reflectance spectroscopy to forage evaluation in ADAS. In: Wiseman J., Cole, D.J.A. (eds) *Feedstuffs Evaluation.* Nottingham Easter School in Agricultural Science No 50, 1989. Butterworths, London, UK, pp. 337–351.

Baker, C.W., Givens, D.I., Deaville, E.R. (1994). Prediction of organic matter digestibility in vivo of grass silage by near infrared reflectance spectroscopy: effect of calibration method, residual moisture and particle size. *Animal Feed Science Technology,* 50: 17–26.

Chang, C.W., Laird, D.A., Mausbach, M.J., and Hurburgh Jr. C.R. (2001). Near infrared reflectance spectroscopy - principal components regression analysis of soil properties. *Soil Science Society America Journal,* 65: 480–490.

Clark, D.H., Mayland, H.F. and Lamb, R.C. (1987). Mineral Analysis of Forages with Near Infrared Reflectance Spectroscopy. *Agronomy Journal*, 79: 485–490.

Corona, E.P., Garcia, L., Garcia, A., Vazquez de Aldana, B.R, and Garcia, B. (1991). Produccion de pastizales en zonas semiaridas segun un gradient topografico, pp.304–309. IN: XXXI Reunion Cientifica de la S.E.E.P. Murcia, *Sociedad Espanola para el Estudio de los Pastos*, Murcia, Spain.

Dardenne, P., Sinnaeve, G., Bollen, L. and Biston, R. (1995). Reduction of wet chemistry for NIR calibrations. Leaping Ahead with Near Infrared Spectroscopy. Royal Australia Chemical Institute, Melbourne, Australia, pp. 154–160.

De Boever, J.L., Cottyn, B.G., De Brabander, J.M., Vanacker, J.M. and Boucque Â C.V. (1997). Prediction of the feeding values of maize silages by chemical parameters, in vitro digestibility and NIRS. *Animal Feed Science and Technology,* 66: 211–222.

De Boever, J.L., Cottyn, B.G. Vanacker, J.M., Boucqué, C.V. (1995). The use of NIRS to predict the chemical composition and the energy value of compound feeds for cattle. *Animal Feed Science Technology,* 51: 243–253.

Foley, W.J., McIlwee A., van Lawler, I., Aragones, L., Woolnough, A.P. and Berding, N. (1998). Ecological application of near infrared reflectance spectroscopy a tool for rapid, cost effective prediction of the composition of plant and animal tissues and aspects of animal performance. *Oecologia,* 116: 293–305.

Givens, D.I., Baker, C.W., Moss, A.R. and Adamson, A.H. (1991). A comparison of near infrared reflectance spectroscopy with three in vitro techniques to predict the digestibility in vivo of untreated and ammonia treated cereal straws. *Animal Production,* 35: 83–94.

Huang, C., Han, L., Yang, Z. and Liu, X. (2009) *Fuel*, 88: 163–168.

Lovett, D.K., Deaville, E.R., Givens, D.I., Finlay, M. and Owena, E. (2005). Near infrared reflectance spectroscopy (NIRS) to predict biological parameters of maize silage: effects of particle comminution, oven drying temperature and the presence of residual moisture. *Animal Feed Science and Technology,* 120: 323–332.

McClure W.F. (2003). 204 years of near infrared technology: 1800–2003. *Journal of Near Infrared Spectroscopy,* 11: 487–518.

Nutrient requirements of horses. (2007). (6. rev. ed.). Washington, D.C: The National Academies Press.

Petisco, C., Garcı´a-Criado, B., Va´zquez de Aldana, B.R., Garcı´a-Ciudad, A. and Mediavilla, S. (2008).

Ash and mineral contents in leaves of woody species: analysis by near-Infrared reflectance spectroscopy. *Communications in Soil Science and Plant Analysis,* 39: 905–925.

Ruano-Ramos, A., Garcia-Ciudad, A., Garcia-Criado, B. (1999) Near infrared spectroscopy prediction of mineral content in botanical fractions from semi-arid grasslands. *Animal Feed Science and Technology,* 77: 331–343.

Shenk, J.S., Landa, I., Hoover, M.R. and Westerhaus, M.O. (1981). Description and evaluation of a near infrared reflectance spectro-computer for forage and grain analysis. *Crop Science,* 21: 355–358.

Shenk, J.S., Workman, J. and Westerhaus, M.O. (1992). Applications of NIR spectroscopy to agricultural products. In: Burns D.A. and Ciurczak E.W. (eds) *Handbook of Near Infrared Analysis*. Marcel Dekker, USA pp. 383–431.

Stone, M. (1974). Cross-Validatory choice and Assessment of Statistical Predictions. *Journal of the Royal Statistical Society*. Ser. B., 36: 111–133.

Subbarao, G.V., Ito, O., Berry, W.L. and Wheeler, R.M. (2003). Sodium- A functional plant nutrient. *Critical Review in Plant Sciences*, 22(5): 391–416.

Vazquez de Aldana, B.R., Garcia Criado, B., Garcia Ciudad, A. and Perez Corona, M.E. (2008). Estimation of mineral content in natural grasslands by near infrared reflectance spectroscopy, *Communications in Soil Science and Plant Analysis*, 26: 9-10: 1383-1396, DOI: 10.1080/00103629509369379.

Vazquez de Aldana, B.R., Garcia Criado, B., Garcia Ciudad, A., and Perez Corona, M.E. (1995). Estimation of mineral content in natural grasslands by near infrared reflectance spectroscopy. *Communications in Soil Science and Plant Analysis,* 26: 1383–1396.

An investigation into precision supplementation of concentrates to grazing Holstein heifers

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Abstract

Achievement of growth targets is crucial to enable dairy heifers to reach critical development goals at the optimal age, to achieve first calving at 24 months. Feed costs are a significant proportion of the rearing costs, thus incentivising more precise and effective use of concentrate supplements. The objective of the study was through precision feeding at grass whilst achieving growth targets, to reduce the variation in weight gain of heifers. Holstein heifers (n=63) were assigned to three treatments across three replicates - individually supplemented, group supplemented and no supplementation. The study commenced on 08 August 2018 and ran for 69 days. In-field precision supplementation hubs allocated concentrates individually, recording several parameters: visit data, water consumption and live weights. Heifer live weights were also manually recorded on a weekly basis. Targeted heifer live weight performance day^{-1} and concentrate supplementation levels were updated weekly. Grass samples were taken weekly for nutritional analysis to calculate concentrate allocation. Heifer behaviour was monitored using Ice Robotics activity sensors, recording standing and lying bouts throughout the duration of the study. All treatments were allocated 1.8% of live weight in grazed grass day^{-1}. The supplemented treatments and the pasture only treatment heifers grew at 1.18 kg day^{-1} and 0.85 kg day^{-1}, respectively ($P < 0.032$). Treatment had an effect ($P < 0.006$) on the utilisation of the pasture. Tailoring supplementation to individual heifers compared with group feeding reduced the mean amount of concentrates used.

Keywords: grazing, heifers, supplementation

Introduction

The ability of heifers to reach puberty, cycle normally and conceive at the desired time is crucial for the physical and economic performance of the heifer rearing process (Brickell *et al.*, 2009). Twenty four months is widely recognised as the optimal age at first calving (AFC) for animal health, productivity, as well as the economic performance through minimising the non-reproductive rearing period (Wathes *et al.*, 2014). Nutrition and breeding management are two important factors in the control of the farmer, to achieve an AFC of 24 months. The consistent achievement of growth targets is imperative to enable dairy heifers to reach critical development goals, at the optimal age to achieve 24 month AFC (Cozler *et al.*, 2009). The management of feeding is especially important post weaning as this is a time of great physiological change when heifers reach sexual maturity. Heifers often experience a growth check post weaning at the start of their first grazing season (Cozler *et al.,* 2009). Grazed grass is a comparably cheap grazed feed source in ruminant livestock systems (Patton *et al.,* 2016). The profitability of such systems is determined by their ability to convert the cheaply produced grass into high quality products whilst maximising grass utilisation (Dillon *et al.,* 2008). The limitations of a grazed grass diet is the inconsistency in its growth and nutritional quality across the season, which can make achieving consistent heifer growth challenging. A common method of overcoming this challenge is the supplementary feeding of concentrates (Boulton *et al.*, 2015). Feed costs are a significant proportion of heifer rearing costs, with concentrate supplements more expensive than grazed grass, thus incentivising more precise and effective use of concentrate supplements. Advancements in precision technology through electronic

identification and automated concentrate feeders, has made the individualised management of cows possible (Hills *et al.,* 2015). Precision feeding allows concentrate supplements to be fed on an individual heifer requirement basis, opposed to a more basic 'flat rate' system (Purcell *et al.*, 2016). Feeding heifers a flat rate of concentrates at grass can increase rearing costs unnecessarily and limit the utilisation of pasture. The objective of this study was to reduce the variation in the weight gain of heifers within a grazing group, through the use of strategic individualised precision feeding. Mobile in-field precision supplementation hubs (Biocontrol, Norway) were designed at AFBI Hillsborough for use in the study. The hypothesis of the study was that: there is less variation in live weight between heifers when they are fed individually; less concentrates are required on a group basis; and pasture utilisation would be significantly higher in the non-supplemented treatment compared against the supplemented treatments.

Materials and methods

This study was carried out on the AFBI Hillsborough research farm, on a 16 ha block of grassland. The experimental design comprised three treatments with three replicates. Holstein heifers (n = 63) were assigned to three treatments in groups of seven, balanced on their age and weight averaging nine months old and 250 kg. The treatments comprised an individually tailored supplementation (IS), a group average supplementation (GS) and no supplementation (NS). The study commenced on 08 August 2018 and continued for 69 days until 16 October 2018. In-field precision supplementation hubs allocated concentrates individually, recording animal visit data, water consumption and live weights at each visit. Heifer live weights were recorded on a manually operated and calibrated weighbridge (Tru Test Ltd, UK) on a weekly basis.

Desired live weight performance per day and concentrate supplementation levels were updated weekly for each heifer on the supplemented treatments. They were calculated on the daily live weight gain required day^{-1} to achieve target live weight gain; pasture dry matter (DM); pasture metablolisable energy (ME); concentrate supplement DM and ME; and optimal grass metablolisable energy intake. A formula was used to calculate energy demands and balanced the level of concentrates with the amount of energy supplied from pasture (T Yan., 2017).

The individually supplemented heifers received meal through the precision feeders, whilst the group average treatment received meal through troughs. Grass quality samples were taken weekly to calculate concentrate allocation. Five samples were taken randomly within the paddock (0.2 m^2 above 4 cm) and were scanned fresh via near infrared spectrometry to determine water soluble carbohydrate (WSC), crude protein (CP), acid detergent fibre (ADF) and metabolisable energy (ME).

All treatments were rotated throughout a system of grazing paddocks on a weekly basis, with the precision supplementation hubs moving with each group. All treatments were allocated a pasture allowance based on 1.8% of live weight in grazed grass kg DM day^{-1}. Paddock length was adjusted to achieve the desired paddock area and calculated based on the kg DM demand of the group. Paddock area was measured using a measuring wheel (Forge Steel, UK) to the nearest 0.1 m.

Compressed sward heights were measured with a rising plate meter (Jenquip, New Zealand) and recorded on animal entry and exit of each paddock. Herbage mass was calculated using a predetermined equation calibrated at AFBI Hillsborough (Dale, 2010) and validated weekly by taking grass clippings (Bosch, UK) of 0.2 m × 1 m across five random plots within each paddock (total 1.0 m^2) cut to an estimated stubble height of 4 cm. Samples collected were weighed fresh and submitted for laboratory analysis to determine the oven DM (dried at 60 °C for 72 h).

Heifer behaviour was monitored using Ice Robotics activity sensors (IceRobotics, UK), recording standing and lying bouts throughout the duration of the study. The data were analysed using GenStat (VSN International, 2015). Data gathered at multiple time points on individual heifers were analysed using a linear mixed model with repeated measures.

Figure 1. A heifer feeding from an in-field precision supplementation hub

Results and discussion

The statistically analysed results are the liveweight records from the Tru Test weighbridge. The heifers on the IS and GS treatments both grew at an average of 1.18 kg day^{-1}, whilst the NS treatment grew 0.33 kg day^{-1} less at 0.85 kg day^{-1} (Table 1).

Treatment had an effect ($P < 0.006$) on the utilisation of the pasture, being lowest in the individually supplemented treatment, increasing by 4% and 6% for the group supplemented and no supplement treatments, respectively (Table 1).

Tailoring supplementation to individual heifers compared with group feeding reduced the amount of concentrate supplement required to achieve similar weight gain by 11.5 kg heifer^{-1} across the study (Table 2). Heifers receiving the individual supplements on average consumed 89% of the amount they were allocated.

Table 1. The effect of concentrate supplementation method on heifer growth and grazing utilisation

	Individual supplement	Group av. supplement	No supplement	SED	P value
Mean live weight (kg)	298	290	283	6.74	0.145
Average weight gain (kg/day)	1.18[a]	1.18[a]	0.85[b]	0.11	0.032
Pasture utilisation (%)	81.6	86.1	88.0	3.1	0.006

The IS, GS and NS treatments reduced the proportion of heifers within each group below

target weight for age by 34%, 38% and 20% respectively (Table 2). The total amount of concentrates consumed over the study period by each individual heifer on the IS treatment ranged from 37 kg to 186 kg, with a group mean of 106 kg (Figure 1).

Table 2. The effect of concentrate supplementation method on concentrate use and group performance

	Individual supplement	Group av. supplement	No supplement
Mean total conc consumed (kg/hd)	106	118	0
Under target weight at start (%)	48	57	53
Under target weight at end (%)	14	19	33

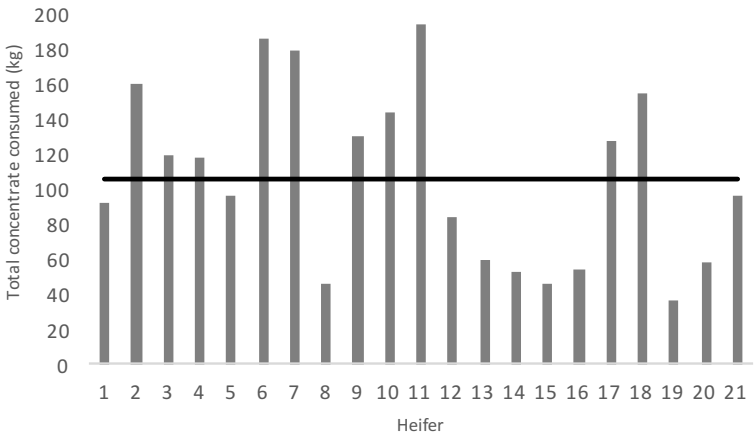

Figure 2. Variation in total concentrates consumed between heifers fed individually across the study period

Tailored individual feeding of concentrates has had a significant role over previous decades within indoors system in increasing production and improving efficiencies, especially regarding dairy cows. This study has highlighted the potential to reduce concentrate use through more specific feeding within a grazing system. Further work to focus on from this study includes tying the feeding behaviour of the heifers on the feeders with the weather data and their activity data.

Conclusion

Pasture utilisation for the supplemented groups was significantly lower than the non-supplemented treatment. The mean concentrate supplement required per heifer for the same mean daily live weight gain was less for the individually supplemented heifers than the group supplemented.

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References

Boulton, A.C., Rushton, J. & Wathes, D.C. (2015). Analysis of the management and costs associated with rearing pregnant dairy heifers in the UK from conception to calving. *Open Journal of Animal Sciences,* 5**:** 474–485.

Brickell, J.S., Bourne, N., Mcgowan, M.M. & Wathes, D.C. (2009). Effect of growth and development during the rearing period on the subsequent fertility of nulliparous Holstein-Friesian heifers. *Theriogenology,* 72**:** 408–416.

Cozler, Y.L., Peyraud, J.L. & Troccon, J.L. (2009). Effect of feeding regime, growth intensity and age at first insemination on performances and longevity of Holstein heifers born during autumn. *Livestock Science,* 124**:** 72–81.

Dillon, P., Hennessy, T., Shalloo, L., Thorne, F. & Horan, B. (2008). Future outlook for the Irish dairy industry: a study of international competitiveness, influence of international trade reform and requirement for change. International Journal of Dairy Technology, 61: 16–29.

Hills, J.L., Garcia, S.C., Rue, B.D. & Clark, C.E.F. (2015). Limitations and potential for individualised feeding of concentrate supplements to grazing dairy cows. *Animal Production Science*, 55: 922–930.

Patton, D., Pierce, K.M. & Horan, B. (2016). Effect of stocking rate on milk and pasture productivity and supplementary feed use for spring calving pasture fed dairy systems. *Journal of Dairy Science*, 99: 5904–15.

Purcell, P.J., Dale, A.J., Gordon, A.W., Barley, J. & Ferris, C.P. (2016). Effects of predicted milk yields sustained by grazed grass on dairy cow performance and concentrate requirements throughout the grazing season. Grass and Forage Science, 71: 389–402.

Wathes, D.C., Pollott, G.E., Johnson, K.F., Richardson, H. & Cooke, J.S. (2014). Heifer fertility and carry over consequences for life time production in dairy and beef cattle. *Animal Science,* 8**:** 91–104.

Analysis of the heat load effects on the individual activity of lactating dairy cows under accumulation of heat load in a naturally ventilated barn

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Abstract

In response to predicted climate change and the growing interest of consumers in livestock farming, the heat load and welfare of dairy cows have become increasingly important. The objective of the study was the investigation of the accumulation of heat load and intensity on the individual activity changes of lactating dairy cows. The results of our analysis constitute the basis for the development of algorithms for early detection of heat load in dairy cows and for the optimization of the barn climate. The study was conducted from June 2015 to May 2017 in a naturally ventilated barn in Germany. The climate was measured at eight locations inside of the barn and the average temperature-humidity index was calculated every ten minutes. The activity of the dairy cows was measured using accelerometers and described with several behavioural traits per cow and day. The statistical models included autocorrelations in time series and cow individual factors (e.g. lactation number, lactation stage etc.). The results of the barn climate measurements showed distinct periods of heat exposure. The dairy cows individually changed their activity depending on the heat load duration and intensity. For example, with increasing heat load the lying time decreased, and the number of steps increased. The accumulation of heat load during three days preceding the measurement day led to less pronounced activity changes at the measurement day. Furthermore, the first lactating cows and the cows in an advanced stage of lactation showed the most pronounced changes in terms of heat load impact.

Keywords: temperature-humidity index, heat load accumulation, cow individual activity, time series analysis

Introduction

To reduce the adverse effects of heat load, it is important for the farmers to know when the cows suffer from heat load and to correspondingly cool cows to help them effectively off-load heat. In addition to physiological thermoregulatory responses to heat load (de Andrade Ferrazza *et al.*, 2017; Toušová *et al.*, 2017), cows change their activity (Brzozowska *et al.*, 2014; Endres and Barberg, 2007) to reduce the production of metabolic heat and sustain their normal body temperature. Currently, the temperature-humidity index (THI) with different thresholds is the standard method to define the intensity of heat load conditions. The study of Heinicke *et al.* (2018) determined a heat load threshold of 67 THI that led to changes in different activity traits of lactating high-yielding dairy cows. Furthermore, this study revealed that the average daily THI, as well as the heat load duration concerning the accumulation of heat load on the measurement day, should be considered for the evaluation of the heat load of cows. West *et al.* (2003) found that during a hot period, the heat load two and three days preceeding the measurement day had a greater impact on milk yield and dry matter intake than the actual values on the measurement day. It would be interesting to analyse the activity response during heat load accumulation

for several days preceeding the measurement day. Generally, the data obtained from activity monitoring systems should be compared with individual cow factors, because they influence the activity of the individual cows (Bewley *et al.*, 2010; Brzozowska *et al.*, 2014; Maselyne *et al.*, 2017). The objective of the study was the investigation of individual activity changes of lactating high-yielding Holstein-Friesian cows regarding the heat load accumulation and intensity in a moderate climate zone.

Material and methods

Barn design and animals

The data were recorded from June 2015 to May 2017. The experimental farm was located in a moderate climate zone in Brandenburg, Germany. The measurements were carried out in a naturally ventilated dairy barn (39 × 18 m) with a loose housing system. The height of the fiber cement roof varied from 6.2 m at the gable peak to approximately 3.6 m at the sides. The barn was equipped with 51 lying cubicles, with a mixture of straw and lime as bedding material, and an automatic milking system (Lely Astronaut A4, Maassluis, Netherlands). Additionally, there was a fan system for cross ventilation (Figure 1). The herd consisted of approximately 51 Holstein-Friesian cows (first to eighth lactation) that had an average daily milk yield of 40.7 ± 6.8 kg per cow.

Barn climate measurements

The ambient temperature and relative humidity within the barn were automatically measured every 10 minutes using EasyLog USB 2+ sensors (Lascar Electronics Inc., Erie, Pennsylvania, USA). The sensors were positioned at eight locations inside the barn (Figure 1) and 3.4 m above the floor. In this study, the THI based on the formula of the National Research Council (1971) was applied:

$$THI = (1.8 \times T+32)-(0.55-0.0055 \times RH) \times (1.8 \times T-26), \quad (1)$$

where T is the dry bulb temperature in °C, and RH is the relative humidity in per cent. The THI calculations of all eight measurement points were averaged afterwards per time point (every 10 min). This resulted in 144 THI values per day to describe the climate conditions inside the barn. In addition, the heat load intensity (THI level) for each time point was categorized as THI < 68 (no heat), 68 ≤ THI < 72 (mild heat), 72 ≤ THI < 80 (moderate heat), and 80 ≤ THI (severe heat) (Armstrong, 1994; Zimbelman and Collier, 2011). The estimated climate effects regarding the average daily THI and the heat load duration per heat load intensity are described in Table 1.

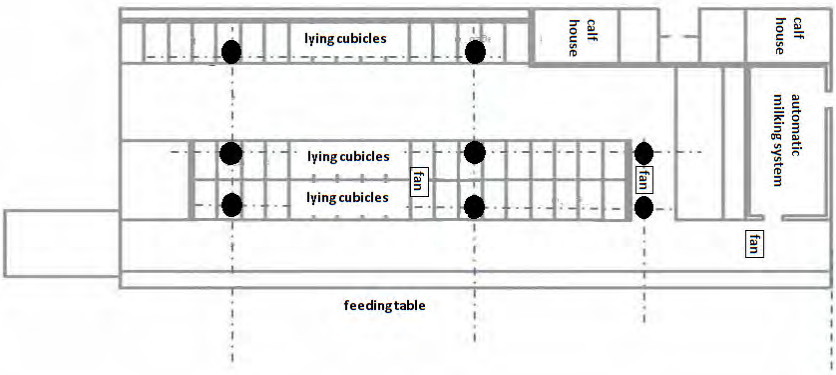

Figure 1. Layout of the naturally ventilated dairy barn with the temperature humidity sensor positions as black points

Table 1. Definition of the estimated climate effects

Contemporaneous heat load effects	
THI_t	Average daily temperature-humidity index (THI) on the measurement day (t)
$HLD_t^{THI\in[68,72)}$	Mild heat load duration (number of time points with 68 ≤ THI < 72 on t)
$HLD_t^{THI\in[72,80)}$	Moderate heat load duration (number of time points with 72 ≤ THI < 80 on t)
$HLD_t^{THI\in>80}$	Severe heat load duration (number of time points with THI ≥ 80 on t)
Delayed heat load effects	
THI_{t-1}	Average daily THI one day preceding the measurement day (t-1)
THI_{t-2}	Average daily THI two days preceding the measurement day (t-2)
THI_{t-3}	Average daily THI three days preceding the measurement day (t-3)
$HLD_{t-1,t-2,t-3}^{THI\in[68,72)}$	Mean mild heat load duration of all three days preceding the measurement day, given that 68 ≤ THI < 72 on at least one time point on each of the three days (t-1, t-2, t-3)
$HLD_{t-1,t-2,t-3}^{THI\in[72,80)}$	Mean moderate heat load duration of all three days preceding the measurement day, given that 72 ≤ THI < 80 on at least one time point on each of the three days (t-1, t-2, t-3)
$HLD_{t-1,t-2,t-3}^{THI\in\geq80}$	Mean severe heat load duration of all three days preceding the measurement day, given that THI ≥ 80 on at least one time point on each of the three days (t-1, t-2, t-3)

Activity measurements

The cows were equipped with an IceTag3D™ activity sensor (IceRobotics, Edinburgh, UK) on one hind leg. The IceTag3D™ is a noninvasive, electronic sensor that measured animal activity with three-dimensional acceleration technology. Per day the activity of 35–50 cows was recorded. Because of the permanent fluctuation of incoming and outgoing cows within the experimental herd, there was a data collection of activity values for in total 196 different cows during the whole experimental period. The analysed activity traits included the total lying time (LT) and the number of steps (NS) per cow and day.

Statistical data analysis

For each activity trait, a linear mixed model was used to test the influence of the contemporaneous and delayed heat load effects on the activity of the cows. In addition, the following individual cow factors were included in the models as a single effect and in interaction with the effects that describe the heat load duration: milk production level ($Milk_t^{low}$; $Milk_t^{normal}$; $Milk_t^{high}$), lactation number (L_t^1; $L_t^{2,3}$; $L_t^{\geq4}$), days in milk (DIM_t^{1-60}; DIM_t^{61-150}; $DIM_t^{>150}$, pregnant status (G_t^0; G_t^{1-90}; G_t^{91-180}; $G_t^{>180}$), estrus status ($I_{t,t-1}^{estrus}$. The reference group included the cows which were classified in all of the following factor levels: L_t^1, DIM_t^{1-60}, $Milk_t^{normal}$, G_t^0, not in estrus. The models incorporated the random effects of the individual cows, and the within-cow temporal correlation structure was modeled by autoregressive-moving-average-processes. The variables were chosen based on the model diagnostics. The model can be written as;

$$
\begin{aligned}
y_{ijklmnt} = \; & \mu + a \cdot THI_t + b \cdot THI_{t-1} + c \cdot THI_{t-2} + d \cdot THI_{t-3} \\
& + Milk_i + L_j + DIM_k + G_l + I_m \\
& + f_{ijkl} \cdot HLD_t^{THI \in [68,72)} + g_{ijkl} \cdot HLD_t^{THI \in [72,80)} + h_{ijkl} \cdot HLD_t^{THI \geq 80} \\
& + i_{ijkl} \cdot HLD_{t-1,t-2,t-3}^{THI \in [68,72)} + j\_ijkl \cdot HLD_{t-1,t-2,t-3}^{THI \in [72,80)} + k\_ijkl \cdot HLD_{t-1,t-2,t-3}^{THI \in \geq 80} \\
& + cow_n + e_{ijklmnt}, \qquad (2)
\end{aligned}
$$

where

$y_{ijklmnt}$ is the observed value of the activity trait; μ is the general mean; *a, b, c, d* are the regression coefficients for the average daily temperature-humidity index *(THI)* on the measurement day *(t)* and one *(t-1)*, two *(t-2)*, and three *(t-3)* days preceding the measurement day; $Milk_i$ is the fixed effect of the *i*-th level of milk production; L_j is the fixed effect of the *j*-th number of lactation; DIM_k is the fixed effect of the *k*-th stage of lactation; G_l is the fixed effect of the *l*-th trimester of pregnancy; I_m is the fixed effect of the *m*-th stage of estrus; f_{ijkl}, g_{ijkl}, h_{ijkl}, i_{ijkl}, j_{ijkl}, k_{ijkl} are the regression coefficients for the interactions of the individual cow factors with the heat load duration *(HLD)* on the measurement day *(t)* and the three days before *(t-1,t-2,t-3)* per heat load intensity; cow_n is the random effect of the *n*-th cow, and $e_{ijklmnt}$ is the random residual.

The null hypotheses for all tested traits were that the contemporaneous and delayed heat load effects, as well as the individual cow factors, had no effect on the activity traits of the dairy cows. The significance level for the linear mixed model was 0.05. All analyses were performed using the free statistical software R version 3.4.2 (R Development Core Team, 2017). The linear mixed models were estimated using the lme-function from the nlme-package (Pinheiro *et al.*, 2014).

Results and discussion

Barn climate conditions

The THI values (at least a period of 10 min) ranged from 20.4 THI to 86.0 THI during the experimental period. The measured climatic conditions were similar to THI values recorded previously in dairy barns in adjacent regions (Ammer *et al.*, 2016; Lambertz *et al.*, 2014). From May to September, heat load duration was strongly pronounced. The heat load duration exceeding the heat load threshold of 68 THI ranged between 84 h month^{-1} and 480 h month^{-1}. In contrast, heat load duration was minimal or zero from October to April. The average THI per month decreased to 37 THI in winter and increased up to 70 THI in summer. Other studies also indicated the highest THI values and the associated heat load from April to September (Gorniak *et al.*, 2014; Lambertz *et al.*, 2014). The longest heat load duration exceeding the heat load threshold of 68 THI was observed in August 2015 (Figure 2). The daily heat load duration of the different heat load intensities showed large differences between the individual days. The daily heat load duration was achieved for up to 24 h for several consecutive days without a relief phase between the days. Therefore, it is recommended for farmers to react with practical mitigation measures like ventilation, cooling or sprinkler systems to reduce heat load during this period. Compared to the existing literature, our study provides additional information to heat load of the cows because of the supplementary specification of heat load duration. The heat load duration includes information on how long the cows were exposed to heat load per day. It will be important to analyse the activity changes during heat load accumulation for several days. Furthermore, the information of daily heat load duration indirectly shows the variance of average THI during the day and therefore, conclusions can be drawn about heat load periods and recovery periods of the cows.

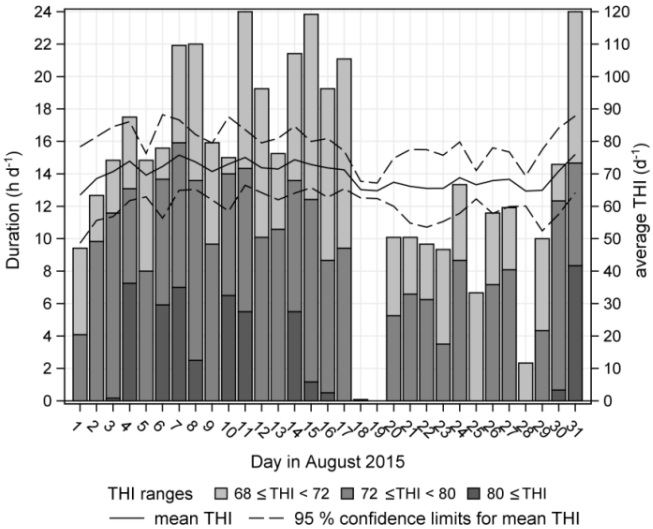

Figure 2. Daily average temperature-humidity index (THI) during August 2015 (mean THI, 95% confidence limits for mean THI), as well as the daily heat load duration regarding the heat load intensities

Changes in the total lying time

The significant results of the linear mixed model for LT are presented in Table 2. Under conditions without heat load on the measurement day and the days before, the daily LT of the cows in the reference group was approximately 647 min. If the characteristics of the cow differed from the reference group, in addition the significant individual cow factors must be taken into account to determine the estimated LT. For example, low-producing cows were found to lie down more than cows with a normal or high level of milk production, and LT in $L_t^{\geq 4}$ increased by 52 minutes d^{-1} compared with LT of cows in earlier lactations. Cows with $DIM_t^{>150}$ lay down approximately 19 minutes per day more than cows with less than 150 DIM. Similar findings have been reported by Bewley *et al.* (2010), Endres and Barberg, (2007), and Maselyne *et al.* (2017). The contemporaneous heat load effects were negatively correlated with LT. In addition to the general negative effect of THI_t, the LT in the herd decreased with increasing intensity and duration of heat load. There was a reduced daily LT to 479 minutes for cows in the reference group with heat load on the measurement day and without heat load the days before. The decrease in LT during heat load conditions agrees with the findings from the literature (Endres & Barberg, 2007; Herbut & Angrecka, 2018). The predicted reduction in LT with increasing severe heat load duration by 10 minutes was higher in cows with $DIM_t^{61\text{-}150}$ and $DIM_t^{>150}$ compared to that in cows with $DIM_t^{1\text{-}60}$. The delayed heat load effects were positively related to LT. The result was that the daily LT of cows in the reference group increased again to 568 minutes when there was heat load on the measurement day and additional heat load during the three days preceding the measurement day. The cows with $L_t^{\geq 4}$ reacted less strongly to increasing moderate heat load duration compared with cows in earlier lactations. Previous studies that analysed the reactions of cows with lying deprivation illustrated the increasing lying motivation and the compensatory reactions (Cooper *et al.*, 2007; Norring & Valros, 2016). They recognised that the cows recovered some of their lost lying time by rescheduling feeding and standing times.

Table 2. The table reports the significant results of the linear mixed model for the total daily lying time in seconds per day depending on the different climate effects and individual cow factors. Standard errors of the predicted coefficients are in parentheses

Individual cow factors		Contemporaneous heat load effects and interactions		Delayed heat load effects and interactions	
$Milk_t^{low}$	1,141.4* (540.1)	THI_t	-192.8* (13.6)	THI_{t-1}	109.1* (13.4)
DIM_t^{61-150}	133.7 (290.5)	$HLD_t^{THI\in[68,72)}$	-23.8* (3.7)	THI_{t-3}	19.1* (9.7)
$DIM_t^{>150}$	1,142.3* (432.2)	$HLD_t^{THI\in[72,80)}$	-47.6* (3.2)	$HLD_{t-1,t-2,t-3}^{THI\in[72,80)}$	30.2* (6.9)
$L_t^{\geq 4}$	3,115.0* (1,102.6)	$HLD_{t-1,t-2,t-3}^{THI\in\geq 80}$	-58.9* (12.7)	x $L_t^{\geq 4}$	-25.7* (9.6)
G_t^{1-90}	1,417.7* (342.4)	x DIM_t^{61-150}	-40.1* (16.1)	$HLD_{t-1,t-2,t-3}^{THI\in\geq 80}$	67.7* (27.4)
G_t^{91-180}	1,088.8* (553.7)	x $DIM_t^{>150}$	-58.3* (17.4)	x $L_t^{\geq 4}$	-80.5* (36.3)
$I_{t,t-1}^{estrus}$	-5,506.7* (282.9)				
* $p < 0.05$ THI values: 99648 activity values: 22221				Intercept	41,797.4* (1,016.5)

Changes in the number of steps

The significant results of the linear mixed model for NS are presented in Table 3. The cows in the reference group had a daily NS of approximately 2,062 steps under climate conditions without heat load on the measurement day and the days before. The NS decreased with increasing DIM, increasing lactation number, and increasing gestation status. Similarly, Brzozowska *et al.* (2014) and Steensels *et al.* (2012) have verified that NS decreases with increasing days in milk. In contrast, the cows in estrus made significantly more steps than cows that were not in estrus. In general, increasing the average daily THI and heat load duration on the measurement day led to an increase in the NS. As a result, the daily NS increased to 2,482 steps when the cows in the reference group were exposed to heat load on the measurement day and without heat load the days before. It agrees with the findings by Endres & Barberg (2007). The contemporaneous heat load effects of mild and moderate heat load duration were dependent on the lactation number. The cows in $L_t^{2,3}$ and $L_t^{\geq 4}$ showed a weaker increase in the NS with increasing heat load duration on the measurement day compared with primiparous cows. In contrast, cows in $G_t^{>180}$ reacted more strongly to moderate heat load duration. The delayed effects of THI_t, moderate and severe heat load duration were negatively related to the NS. However, THI_{t-2} was positively related to the NS. Consequently, the predicted daily NS for the cows in the reference group decreased to 2,207 steps under heat load on the measurement day and additional heat load during the three days preceding the measurement day. The delayed heat load effect

of mild heat load duration was dependent on the milk production level, and the effect of moderate heat load duration was dependent on the lactation number.

Table 3. The table reports the significant results of the linear mixed model for the logarithmized number of steps per day depending on the different climate effects and individual cow factors. Standard errors of the predicted coefficients are in parentheses

Individual cow factors		Contemporaneous heat load effects and interactions		Delayed heat load effects and interactions	
$Milk_t^{low}$	-0.0218	THI_t	0.0013*	THI_{t-1}	-0.0022*
	(0.0216)		(0.0006)		(0.0007)
DIM_t^{61-150}	-0.0453*	$HLD_t^{THI\in[68,72)}$	0.0014*	THI_{t-2}	0.0016*
	(0.0112)		(0.0003)		(0.0007)
$DIM_t^{>150}$	-0.0609*	x $L_t^{2,3}$	-0.0007*	$HLD_{t-1,t-2,t-3}^{THI\in[68,72)}$	0.0001
	(0.0169)		(0.0004)		(0.0003)
$L_t^{2,3}$	-0.1164*	x $L_t^{\geq 4}$	-0.0012*	x $Milk_t^{low}$	0.0014*
	(0.0365)		(0.0004)		(0.0005)
$L_t^{\geq 4}$	-0.3892*	$HLD_t^{THI\in[72,80)}$	0.0015*	$HLD_{t-1,t-2,t-3}^{THI\in[72,80)}$	-0.0019*
	(0.0448)		(0.0003)		(0.0003)
G_t^{1-90}	-0.0509*	x $G_t^{>180}$	0.0024*	x $L_t^{2,3}$	0.0009*
	(0.0134)		(0.0012)		(0.0003)
G_t^{91-180}	-0.0532*	x $L_t^{2,3}$	-0.0006*	x $L_t^{\geq 4}$	0.0020*
	(0.0219)		(0.0003)		(0.0004)
$G_t^{>180}$	-0.0928	x $L_t^{\geq 4}$	-0.0009*	$HLD_{t-1,t-2,t-3}^{THI\in\geq 80}$	-0.0013*
	(0.0498)		(0.0004)		(0.0005)
$I_{t,t-1}^{estrus}$	0.5204*	$HLD_{t-1,t-2,t-3}^{THI\in\geq 80}$	0.0011*		
	(0.0118)		(0.0003)		
				Intercept	7.5993*
* $p < 0.05$	THI values: 99648	activity values: 22221			(0.0410)

Conclusions

Our study confirmed that increasing duration and intensity of heat load led to a decrease in the lying time and an increase in the number of steps. In addition to earlier studies, we included a novel assessment of the influence of delayed heat load effects and individual cow factors under heat load on dairy cow activity. The cows showed a reduced activity response to heat load, when there was additional heat load accumulation during the three days preceding the measurement day. Our study found cow individual activity responses to heat load. The primiparous cows and the cows within an advanced stage of lactation reacted most sensitively to heat load. The heat load accumulation as well as individual cow factors should be considered in prediction models for sensitive animal-specific recognition of heat load based on information on activity responses.

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References

Ammer, S., Lambertz, C., Gauly, M. (2016). Is reticular temperature a useful indicator of heat stress in dairy cattle? *Journal of Dairy Science,* 99: 10067–10076.

Armstrong, D.V. (1994). Heat Stress Interaction with Shade and Cooling. *Journal of Dairy Science,* 77: 2044–2050.

Bewley, J.M., Boyce, R.E., Hockin, J., Munksgaard, L., Eicher, S.D., Einstein, M.E., Schutz, M.M. (2010). Influence of milk yield, stage of lactation, and body condition on dairy cattle lying behaviour measured using an automated activity monitoring sensor. *Journal of Dairy Research*, 77: 1–6.

Brzozowska, A., Łukaszewicz, M., Sender, G., Kolasińska, D., Oprządek, J. (2014). Locomotor activity of dairy cows in relation to season and lactation. *Applied Animal Behaviour Science,* 156: 6–11.

Cooper, M., Arney, D., Phillips, C. (2007). Two-or four-hour lying deprivation on the behavior of lactating dairy cows. *Journal of Dairy Science,* 90: 1149–1158.

De Andrade Ferrazza, R., Garcia, H.D.M., Aristizábal, V.H.V., de Souza Nogueira, C., Veríssimo, C.J., Sartori, J.R., Sartori, R., Ferreira, J.C.P. (2017). Thermoregulatory responses of Holstein cows exposed to experimentally induced heat stress. *Journal of Thermal Biology,* 66: 68–80.

Endres, M.I., Barberg, A.E. (2007). Behavior of dairy cows in an alternative bedded-pack housing system. *Journal of Dairy Science*, 90: 4192–4200.

Gorniak, T., Meyer, U., Südekum, K.-H., Dänicke, S. (2014). Impact of mild heat stress on dry matter intake, milk yield and milk composition in mid-lactation Holstein dairy cows in a temperate climate. *Archives of Animal Nutrition,* 68: 358–369.

Heinicke, J., Hoffmann, G., Ammon, C., Amon, B., Amon, T. (2018). Effects of the daily heat load duration exceeding determined heat load thresholds on activity traits of lactating dairy cows. *Journal of Thermal Biology,* 77: 67.

Herbut, P., Angrecka, S. (2018). The effect of heat stress on time spent lying by cows in a housing system. *Annals of Animal Science,* 18: 825–833.

Lambertz, C., Sanker, C., Gauly, M. (2014). Climatic effects on milk production traits and somatic cell score in lactating Holstein-Friesian cows in different housing systems. *Journal of Dairy Science,* 97: 319–329.

Maselyne, J., Pastell, M., Thomsen, P.T., Thorup, V.M., Hänninen, L., Vangeyte, J., Van Nuffel, A., Munksgaard, L. (2017). Daily lying time, motion index and step frequency in dairy cows change throughout lactation. *Research in Veterinary Science*, 110: 1–3.

National Research Council, A guide to environmental research on animals, National Academy of Science, Washington, DC (1971).

Norring, M., Valros, A. (2016). The effect of lying motivation on cow behaviour. *Applied Animmal Behaviour Science*, 176: 1–5.

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D. (2014). Linear and nonlinear mixed effects models. *R package version 3*.

R Development Core Team, R (2017) A language and environment for statistical computing. Vienna, Austria: *R Foundation for Statistical Computing*, ISBN3-900051-07-0 https://www.R- project.org/ (accessed 10.10.18)

Steensels, M., Bahr, C., Berckmans, D., Halachmi, I., Antler, A., Maltz, E. (2012). Lying patterns of high producing healthy dairy cows after calving in commercial herds as affected by age, environmental conditions and production. *Applied Animal Behaviour Science,* 136: 88–95.

Toušová, R., Ducháček, J., Stádník, L., Ptáček, M., Pokorná, S. (2017). Influence of Temperature- Humidity Relations During Years on Milk Production and Quality. *Acta universitatis agriculturae et silviculturae mendelianae brunensis,* 65: 211–218.

West, J., Mullinix, B., Bernard, J. (2003). Effects of hot, humid weather on milk temperature, dry matter intake, and milk yield of lactating dairy cows. *Journal of Dairy Science,* 86: 232–242.

Zimbelman, R., Collier, R. (2011). Feeding strategies for high-producing dairy cows during periods of elevated heat and humidity, Proceedings of the *20th Annual Tri-State Dairy Nutrition Conference*, Grand Wayne Center, Fort Wayne, Indiana, USA, 19-20 April, 2011. Ohio State University, 111–126.

Dairy cow welfare – perceptions vary significantly between key industry stakeholder groups

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Abstract

ProWelCow (DAFM RSF - A 14/S/890), a nationally funded research project, was set up to investigate risks and strategies to protect/improve the welfare of Irish dairy cows. A questionnaire was conducted with dairy farmers (F; n = 115), cattle veterinarians (V; n = 60) and Teagasc dairy advisors (A; n = 48). The 223 respondents were asked, 1) Do you perceive that expansion in the dairy industry poses concerns for dairy cow welfare? 2) Identify the main causes of poor welfare in cows and, 3) Rank in order of importance the main reasons for culling. A high proportion (c. 80%) of respondents in all groups agreed that expansion poses challenges for cow welfare ($P > 0.05$). The majority of farmers (22.6%) chose poor body condition as the 1° welfare issue; advisors (10.4%) and vets (8.3%), ($P < 0.001$). The majority of advisors (43.8%) chose social stress, different to farmers (14.8%, $P < 0.05$) but not to vets (30.0%), ($P > 0.05$). The highest proportion of vets selected lameness as a primary welfare issue (28.3%); differed from advisors (2.1%) and farmers (13.0%) ($P = 0.001$). The main reason for culling cows was infertility, followed by lameness and mastitis/high SCC. Vets ($P = 0.01$) and advisors ($P = 0.021$) perceived infertility as the primary reason for culling more often than farmers. There was a lack of consensus regarding the importance of lameness and poor BCS between stakeholders. This was surprising, and worrying, but probably reflects the differing focus/areas of expertise between the groups. Given these results, greater cross-dialogue between stakeholder groups is required.

Keywords: dairy cow welfare, dairy herd expansion, survey, veterinarians, advisors, farmers

Introduction

The predominant model of dairy farming practised in Ireland is a pasture-based, seasonal (spring-calving) milk production system. Scientific evidence suggests that there are advantages and disadvantages to dairy cow welfare and reproductive performance associated with pasture-based systems of milk production (Olmos *et al.*, 2009a, b, Mee, 2012; Arnott *et al.*, 2017). However, consumers perceive pasture-based systems as 'natural' and therefore better for cow welfare than confinement systems. This offers a marketing advantage to Irish dairy products. Irish systems of milk production will also have an advantage over countries in which milk is primarily produced from confined cows should legislation protecting cow welfare (and favouring pasture-based systems) be passed in the EU. It is speculated that such legislation would ensure that all dairy cows have some outdoor access. Such advantages could be threatened by expansion in the Irish dairy industry arising from the abolition of the EU milk quota (2015) because of associated risks to cow welfare. One of the main features of expansion *de facto* is larger herd sizes which are likely to be associated with higher stocking densities, lower number of labour units/cow and possibly longer walking distances (Boyle and Rutter, 2013). These characteristics have potential negative implications for dairy cow welfare (Oltenacau and Broom, 2010), particularly in terms of lameness (Barker *et al.,* 2009) but also in terms of metabolic, climatic and social stress and health and welfare in the peri-parturient period (Boyle and Rutter, 2013). One of the first steps in addressing such potential problems comes from an understanding of levels of awareness amongst key stakeholders about cow welfare (Kauppinen *et al.,* 2010).

Hence, the aim of this study was to evaluate perceptions about risks to welfare associated with expansion and the main challenges to dairy cow welfare associated with expansion.

Materials and methods

Three versions of a questionnaire of approximately 40 questions were developed. Questions in each version were tailored to the stakeholders/respondents group, tested and modified accordingly in conjunction with Teagasc dairy research and specialist advisory staff. The survey was conducted in the summer of 2015 with dairy farmers (n = 115) at two national farming events (The National Ploughing Championships and the Moorepark Open Day) and cattle veterinarians (n = 60) at the Cattle Association of Veterinary Ireland Conference by interview. The survey was distributed amongst Teagasc dairy advisors (n = 48) at the beginning of an in-service training day at Moorepark. The advisors were asked to complete the survey themselves at the beginning of the day and the completed forms were collected by the researchers immediately afterwards. The researchers were available to answer queries while the advisors completed the survey.

Some questions were prompted, while others were open-ended. Regarding the latter, some irrelevant and obscure answers were obtained. These were omitted from the analysis. In the case of many of the questions, the answers obtained from dairy farmers related to the situation on their own farm at that time. In contrast, similar questions put to the advisors and vets captured information on their opinions as related to their background knowledge of the issue. This paper relates to the findings of three specific questions: namely, 1) Do you perceive that expansion in the dairy industry poses concerns for dairy cow welfare? (yes/no); 2) Identify the main causes of poor welfare in cows from the following list: lameness, poor body condition score, social stress due to overcrowding, mastitis, metabolic disorders, infectious diseases, cold stress and calving difficulties and, 3) number in order of importance of the main reasons for culling from the following list: infertility, lameness, mastitis/high SCC and other.

Statistical analysis

A Chi-Square Fisher test, (PROC FREQ, SAS), was used to investigate whether distributions of response frequencies differed between respondents. Relative standard errors (RSE) were calculated to estimate the precision of the estimates. Data in tables were compared statistically across rows (not down columns) between stakeholder groups.

Results

1) Do you perceive that expansion in the dairy industry poses concerns for dairy cow welfare?

A high proportion of respondents in all three groups reported that expansion in the dairy industry poses concern for cow welfare. This did not differ between stakeholder groups ($P > 0.05$) (Table 1).

Table 1. Opinions of advisors, farmers and cattle vets (%+RSE) as to whether there is a cause for concern about cow welfare in expanding Irish dairy herds*

	Advisors	Farmers	Vets
Yes	81.3±5.7	79.1±3.8	85.0±4.6
No	12.5±4.8	20.9±3.8	13.3±4.4

*Note, column totals do not add up to 100% because some respondents did not answer the question.

2) Identify the main causes of poor welfare in cows

Poor body condition was rated as a primary cause of poor welfare in dairy cows by the majority of farmers, while lameness was rated as a primary cause by the majority of vets (Table 2). Social stress due to overcrowding was selected as the primary reason for poor welfare by dairy advisors. It was equally important for advisors and vets, while less important for farmers ($P < 0.05$). Advisors did not agree with vets on the importance of calving difficulties for cow welfare ($P = 0.013$). Note, comparisons in Table 2 are made across rows, not down columns. Hence, while numerically more vets selected social stress than lameness or poor body condition as the primary cause of poor welfare, relative to farmers and advisors, more vets selected lameness as the primary cause of poor welfare i.e. row comparison.

Table 2. Opinions of advisors, farmers and cattle vets (%+RSE) as to the primary cause of poor welfare in Irish dairy cows*

Primary cause of poor welfare in dairy cows	Advisors	Farmers	Vets
Lameness	2.1±2.1[a**]	13.0±3.2[a]	28.3±5.9[b]
Poor body condition	10.4±4.5[ab]	22.6±3.9[a]	8.3±3.6[b]
Social stress due to overcrowding	43.8±7.2[a]	14.8±3.3[b]	30.0±6.0[a]
Calving related disorders or difficulties	18.8±5.7[a]	8.7±2.6[ab]	1.7±1.7[b]
Mastitis	2.1±2.1	10.4±2.9	3.3±2.3
Metabolic disorders	2.1±2.1	2.6±1.5	0.0
Cold stress	2.1±2.1	1.7±1.2	1.7±1.7
Infectious diseases	4.2±2.9	13.0±3.2	6.7±3.2

*Note, column totals do not add up to 100% because some respondents did not answer the question or provided only one primary cause. **Values with superscripts differ significantly within rows

3) Number in order of importance of the main reasons for culling in your herd

The main reason for culling cows on farms was infertility, followed by lameness and mastitis/high somatic cell count (Table 3). Vets ($P = 0.01$) and advisors ($P = 0.021$) perceived infertility as the primary reason for culling more often than reported by farmers. Vets and advisors agreed with farmers regarding mastitis/high somatic cell count as a reason for culling. The main disagreement between farmers and the other two groups related to lameness (with advisors: $P = 0.05$ and with vets $P = 0.031$). Almost 14% of farmers reported lameness as the main reason for culling their dairy cows while none of the advisors and only one vet cited it as the main reason for culling.

Table 3. Opinions of advisors and cattle vets (%+RSE) about the main reasons for culling cows in Irish herds and the actual reasons for culling as reported by the surveyed farmers*

Primary reason for culling	Perceptions		Reported
	Advisors	Vets	Farmers
Infertility	81.3±5.7[a**]	81.7±5[a]	61.7±4.6[b]
Lameness	0[b]	1.7±1.7[b]	13.9±3.2[a]
High somatic cell count/mastitis	14.6±3.7	11.7±2.2	12.2±1.6
Poor performance	0	1.7±1.7	0
Other	0	0	1.8±0.9

*Note, column totals do not add up to 100% because some respondents did not answer the question or provided only one primary cause. **Values with superscripts differ significantly within rows

Discussion

It is perhaps not surprising to discover that members of all stakeholder groups equally (~80%) perceived that expansion in the dairy industry posed concerns for dairy cow welfare given the relatively close contact between Irish farmers and cattle vets and farmers and advisors. This suggests that within the Irish dairy industry a broad consensus exists that even in a predominantly pasture-based system, herd expansion may have detrimental effects on cow welfare. However, a substantial minority of respondents across groups did not hold this opinion suggesting that herd expansion was perceived as a neutral or even a positive effect on cow welfare. Unfortunately, the question posed did not allow the latter detail to be disaggregated within the answer.

Causes of poor welfare

All the welfare issues presented were selected by a proportion of the respondents as potentially important causes of poor cow welfare to a greater or lesser extent. Given these results, further research needs to focus on the identified primary causes of poor welfare in pasture-based dairy cows.

While stakeholders agreed that herd expansion posed concerns about cow welfare, they disagreed on the details of these concerns which is in line with findings of Leonard *et al.* (2001). Farmers were most concerned about poor body condition. This result corresponds well to the findings of the survey by Leonard *et al.* (2001) where 64% of farmers ranked nutrition as the primary contributor to good welfare in dairy cows. This finding may reflect farmers concerns about relying on grass as the main source of feed whilst simultaneously trying to increase milk production under a no-quota regime. With volatile milk prices this affects their financial capacity to supplement grass with purchased feed. They may also be concerned about a reduction in cow body condition affecting cow fertility given its effect on cow culling.

There is poor consensus in the literature as to the welfare implications of poor body condition (Roche *et al.*, 2009). While thin cows possibly feel tired and unwell (Webster, 1995) it is unlikely that they are actually in pain. However, if thin cows are concurrently hungry they are likely to be suffering from very poor welfare. Indeed, the concern about body condition expressed by farmers could be linked to memories of the national fodder crisis in 2013 when maintaining body condition on cows was particularly challenging. However,

low body condition is a problem inherent to high grass/low concentrate diets particularly in early to peak lactation (as well as in times of grass shortages due to drought/cold) (Webster *et al.,* 2008). The concern expressed by farmers could simply reflect an inherent association between poor body condition and suffering. Irrespective of whether or not thin cows are actually suffering from poor welfare, poor body condition is an issue which farmers, and likely the public, are concerned about and one which needs to be addressed if the positive image of pasture-based dairying systems is to be protected and farmers' social licence to farm maintained.

Farmers differed significantly from vets in their appreciation of poor body condition as a welfare concern for dairy cows. While the difference between farmers and advisors was not significant, 50% fewer advisors cited poor body condition as the primary cause of poor welfare than farmers. This disparity between farmers and the other stakeholder groups on poor body condition suggests that farmers uniquely perceive the associated welfare implications because they uniquely suffer the economic consequences of poorer milk production, subfertility and ultimately, premature culling.

There is widespread recognition that owing to its high prevalence and the associated pain, lameness is the primary welfare condition of dairy cows (EFSA, 2009). Cattle vets were in agreement with this view with a significantly higher proportion citing lameness as a main cause of poor welfare compared to farmers or advisors. Given the extensive literature on lameness and its importance as a production disease in dairy herds it is perhaps not surprising that vets should view it as a primary concern. This, allied to their clinical experiences of being called out to treat lame cows, probably informed their views. A more surprising finding was the lack of responses from advisors citing lameness as a welfare concern. This may be because they view lameness as a 'disease' not a 'welfare' issue or because they are not exposed to lame cows in their daily work and so underestimate its importance. Nevertheless, the very low proportion of both advisors and farmers citing lameness as the primary cause of poor welfare in dairy cows poses concerns in addressing this painful and highly prevalent condition (EFSA, 2009) irrespective of production system (Whay *et al.,* 2003).

There was a clear (and significant) divergence of opinion between farmers on the one hand and advisors and vets on the other about social stress due to overcrowding. This may be due to the perception by the latter stakeholders that herd expansion would inevitably lead to overcrowding while farmers may have a blind spot about the importance of this concern. This is supported by findings that while 77% of the farmers surveyed had increased their herd size, 33% did not provide a cubicle per cow during the winter housing period. This may be an example of 'farm blindness'. Farm blindness is a perception by farmers that what they see every day on their own farm is normal, particularly when it is not; a new normal (Mee, 2019). In contrast, both vets and advisors showed an awareness of the potential link between expansion and an increase in stocking densities with no difference between these groups in the proportion that cited social stress as the main welfare problem for cows in expanding herds. This problem was by far the most common welfare problem for dairy cows cited by dairy advisors. It appears that they may have linked the lack of investment in housing in expanded dairy herds with the potential risk of overcrowding.

Clinical mastitis is a highly prevalent health problem in Irish dairying systems (Geary *et al.,* 2013). The low number of respondents in all stakeholder groups who indicated mastitis as a primary cause of poor welfare may reflect a lack of awareness about the pain implications of this condition. On the other hand, the results may also reflect the stakeholders' perception of issues such as mastitis as health rather than welfare problems. Similarly, issues such as metabolic disorders, infectious diseases and disorders around calving traditionally have more health rather than welfare connotations and very few

were selected by respondents as being of importance to cow welfare. However, most of these conditions also impact on animal welfare, for example, increased dystocia (Leonard *et al.*, 2001) and perinatal calf mortality (Mee *et al.,* 2013).

The difference between advisors and vets on the importance of calving difficulties (dystocia) as welfare concerns, where advisors perceived them to be more important than did vets, may stem from the lived experiences of these two groups. Irish cattle vets will have seen the decline in the number of calls to dystocia in dairy herds over the last decade primarily due to changes in breeding policies (less use of beef sires in dairy herds, genetic selection against long gestation length, stillbirth and calving difficulty, introgression of Jersey genetics). Advisors may not be as aware of the effects of these changes in this specific aspect of farm management, hence, their greater perception of its current importance as a welfare concern.

Reasons for culling cows

In spite of significant advances made in improving the fertility performance of Irish dairy cows, these results indicate that infertility still remains the main reason for culling. This corresponds well with international data from other production systems (Whitaker *et al.,* 2004). A significantly higher proportion of farmers reported lameness as a main reason for culling than perceived by the advisors or vets. These findings may indicate an under appreciation amongst dairy advisors and vets as to the contribution lameness makes to culling on Irish dairy farms. Amongst UK dairy cows, Whitaker *et al.* (2004) found lameness to be the third most common reason for culling after mastitis and infertility. In many cases there is more than one reason for culling, particularly as many animals are infertile or have poor milk yields because they are lame (EFSA, 2009). Indeed lameness as a main reason for culling was probably underestimated by the farmers themselves as cows that are culled for infertility or mastitis can also be lame but lameness will only be recorded as a secondary cause of culling, if at all. A similar proportion of farmers cited lameness and mastitis as the main reasons for culling. This may reflect, in part, on the national mastitis awareness campaign (*CellCheck* by Animal Health Ireland) and the relatively high incidence of lameness in Irish dairy herds.

Conclusions

There is a lack of consensus amongst key stakeholders on the causes of poor welfare in dairy cows. There is also a lack of awareness about main reasons for culling dairy cows by advisors and vets relative to farmers' lived experiences. This probably reflects the differing focus and areas of expertise between the three groups surveyed. From the results of these surveys it is likely that poor body condition, overcrowding during housing and lameness are all important causes of poor cow welfare in expanding, low cost, pasture-based systems.

References

Arnott, G., Ferris, C.P. and O'Connell, N.E. (2017). Welfare of dairy cows in continuously housed and pasture-based production systems. *Animal,* 11(2): 261–273.

Barker, Z.E., Amory, J.R., Wright, J.L., Mason, S.A., Blowey, R.W., & Green, L.E. (2009). Risk factors for increased rates of sole ulcers, white line disease, and digital dermatitis in dairy cattle from twenty-seven farms in England and Wales. *Journal of Dairy Science*, 92(5): 1971–1978.

Boyle, L.A. and Rutter, S.M. (2013). Comparison of the welfare of dairy cows in 'pasture based' and 'zero grazed' milk production systems. Profitable and sustainable grazing systems – moving forward with science. *Joint BGS and BSAS conference*, Malvern, UK pp. 11–14.

European Food Safety Authority (2009). Scientific opinion on welfare of dairy cows in relation to leg and locomotion problems based on a risk assessment with special reference to the impact of housing, feeding, management and genetic selection. *EFSA Journal*, 1142: 1–57.

Geary, U., Lopez-Villalobos, N., O'Brien, B., Garrick, D. and Shaloo, L. (2013). Examining the impact of mastitis on the profitability of the Irish dairy industry. *Irish Journal of Agricultural and Food Research*, 52: 135–149.

Kauppinen, T., Vainio, A., Valros, A., Rita, H. and Vesala, K.M. (2010). Improving animal welfare: qualitative and quantitative methodology in the study of farmers' attitudes. *Animal Welfare*, 19(4): 523.

Leonard, N., Egan, J., Griffin, J., A. H and Poole, D. (2001). A survey of some factors relevant to animal welfare on 249 dairy farms in the Republic of Ireland. Part 2: data on incidence of disease, culling and biosecurity measures. *Irish Veterinary Journal,* 54: 454–456.

Mee, J.F. (2012). Reproductive issues arising from different management systems in the dairy industry. *Reproduction in Domestic Animals*, 47: 42–50.

Mee, J.F. (2013). Why do so many calves die on modern dairy farms and what can we do about calf welfare in the future? *Animals*, 3: 1036–1057.

Mee, J.F. (2019). Invited Review: Denormalising poor dairy youngstock management – dealing with 'farm-blindness' *Journal of Animal Science* (in press).

Olmos, G., Mee, J.F., Hanlon, A., Patton, J., Murphy, J.J. and Boyle, L.A. (2009a). Peripartum health and welfare of Holstein-Friesian cows in a confinement TMR system compared to a pasture based system. *Animal Welfare,* 18: 467–476.

Olmos, G., Boyle, L.A., Hanlon, A., Patton, J., Murphy, J. and Mee, J. (2009b). Hoof disorders, locomotion ability and lying times of cubicle-housed compared to pasture-based dairy cows *Livestock Science,* 125: 199–207.

Oltenacu, P.A. and Broom, D.M. (2010). The impact of genetic selection for increased milk yield on the welfare of dairy cows. *Animal Welfare*, 19(1): 39–49.

Roche, J.R., Friggens, N.C., Kay, J.K., Fisher, M.W., Stafford, K.J., & Berry, D.P. (2009). Invited review: Body condition score and its association with dairy cow productivity, health, and welfare. *Journal of Dairy Science*, 92(12): 5769–5801.

Webster, J. (1995). "*Animal welfare: a cool eye towards Eden*."

Webster, J. (2008). *Animal Welfare: limping towards Eden: A practical approach to redressing the problem of our dominion over the animals.* John Wiley & Sons.

Whay, H.R., Main, D.C.J., Green, L.E., & Webster, A.J.F. (2003). Assessment of the welfare of dairy cattle using animal-based measurements: direct observations and investigation of farm records. *Veterinary Record*, 153(7): 197–202.

Whitaker, DA, Macrae, AI, Burrough, E (2004). Disposal and disease rates in British dairy herds between April 1998 and March 2002. *Veterinary Record* 155: 43–5.

Using the SMARTBOW system for monitoring animals suffering from periparturient disease

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Abstract

Around parturition, 30–50% of dairy cows are affected by metabolic and/or infectious diseases. Hence, routine and proactive actions by farmers and veterinarians are intended to accurately and efficiently provide early detection of disorders. Nowadays, various sensor systems are available to assist the farmer in herd management decisions. Applying these technologies targets an improved health monitoring to secure high levels of animal welfare, ensure food quality and safety as well as in optimising work efficiency.

The sensor system SMARTBOW (Smartbow GmbH, Weibern, Austria) consists of a 3D-accelerometer. Commercial features include estrus detection, rumination monitoring and localisation of animals in the barn.

In this study the SMARTBOW system was used for retrospectively describing activity levels, rumination and distinct behaviours of diseased animals compared with their 'healthy' controls. For this, the system was installed in a commercial dairy farm, housing approx. 2,700 Holstein Friesian cows. Animals were enrolled at drying off and followed up to 70 days after parturition. Besides body condition scoring and metabolic testing, animals were clinically examined daily during the first eight days of lactation. Findings (e.g. rectal temperature, ß-hydroxybutyrate concentration) and diagnoses (e.g. Hypocalcemia, Ketosis, Metritis, Mastitis) were recorded and the data of 316 animals were used for statistical analyses.

During the transition period, numerical differences in the average daily rumination time were observed between animals suffering from disorders and their matched healthy controls. Further in-depth analyses of the SMARTBOW data with and without considering combinations of captured parameters are currently in progress.

Keywords: cow, transition period, health monitoring, accelerometer

Introduction

Around parturition 30–50% of dairy cows are affected by metabolic and/or infectious diseases (Leblanc, 2010). Besides being detrimental from an animal welfare's perspective, disorders in early lactation have a negative effect on animal health, milk production and reproductive performance (Fourichon *et al.*, 1999; Rajala-Schultz *et al.*, 1999; Vercouteren *et al.*, 2015), and are associated with significant economic losses (Kaneene & Scott Hurd, 1990; Ingvartsen, 2006). An often occurring problem in practice is the underestimation of a disease on farm level. Hence, routine proactive management measures are recommended to precisely and efficiently detect health problems which, in turn, allow an early intervention and treatment of the animals. These measures are aimed to limit the consequences of health problems on herd performance as well as on animal health and welfare (LeBlanc, 2006).

Several standard operating procedures (SOP) were recommended, defining which animal,

how and in which specific time period should be examined (Cook *et al.*, 2006a, b; Leblanc, 2010). Even if these procedures are standardised, the examination of animals is time consuming and their success relies on the experience and willingness of the farmer or his/her personnel, if applicable to strictly follow the SOPs. In this context, automated and continuous monitoring systems may complement health-monitoring programs and provide additional information that can be used to improve the management of individual cows or the entire herd (Rutten *et al.*, 2013; Lukas *et al.*, 2015). Nowadays, various sensor systems are available to assist the farmer in herd management decisions. Applying these technologies targets an improved health monitoring to secure high levels of animal welfare, ensure food quality and safety as well as in optimising work efficiency (Wathes *et al.*, 2008; Bewley, 2010).

The sensor system SMARTBOW (Smartbow GmbH, Weibern, Austria) consists of a 3D-accelerometer. Based on machine learning algorithms, commercial features (based on 1 Hz accelerometer) include estrus detection, rumination monitoring and localisation of animals in the barn, so far.

The aim of this study was to evaluate if the outputs parameter of the accelerometer system SMARTBOW are eligible for early disease detection in periparturient cows.

Material and methods

All study procedures were approved by the institutional ethics committee of the University of Veterinary Medicine Vienna, Austria, in accordance with the national authority according to § 26 of the Law for Animal Experiments, Tierversuchsgesetz 2012 – TVG 2012 (BMWFW-68.205/0004-WF/V/3b/2016), as well as by the Slovakian Regional Veterinary Food Administration.

Herd description

The study was conducted on a Slovakian dairy farm, housing approximately 2,700 Holstein-Friesian cows. Cows were kept in groups of up to 250 animals and had no access to pasture. The average energy corrected milk yield (based on 4.0% butterfat and 3.4% protein) was 9,260 kg per cow in 2018. Dry cows were housed in group pens on straw bedding. Lactating cows were kept in ventilated freestall barns, equipped with full concrete floors and high bed cubicles. Cows had *ad libitum* access to water and were fed a total mixed ration consisting of corn silage, alfalfa silage, beet pulp silage, wet distiller's grains with solubles, corn-cob-mix, rapeseed extraction meal, and minerals. All animal related events (e.g. calving date, calving ease, clinical diseases, treatments) were entered into the herd management software DairyComp 305 (DC305, Valley Agricultural Software, Tulare, USA) by responsible farm personnel. First lactating cows gave birth at another farm site, thus, only multiparous cows were included in this study.

SMARTBOW system

The SMARTBOW ear-tag (Smartbow GmbH, Weibern, Austria) contains a 3D-accelerometer which collects data from cow head and ear movements that are processed and used for continuous automated real-time monitoring. So far, the system has been evaluated for activity measurement, rumination monitoring (Borchers *et al.*, 2016; Reiter *et al.*, 2018) and localisation (Wolfger *et al.*, 2017).

For study purposes, the SMARTBOW system was installed in the 'close-up' and 'fresh cow' pen on the farm. Approximately three weeks prior to parturition (i.e. while regrouping into the 'close-up' pen) the ear-tag based accelerometers were permanently attached to the study animals in the middle of the right ear. Three dimensional acceleration data (range -2 g to +2 g) of head and/or ear movements of the animals were recorded with a frequency

of 10 Hz and sent in real-time to receivers (SMARTBOW WallPoints) installed at a distance of approx. 20 m each, throughout the study pens. Receivers were connected with a local farm server (SMARTBOW FarmServer), on which data were processed.

Study design

In total, 500 multiparous cows were enrolled in the study at drying off at approx. six weeks prior to parturition and followed up until 70 days in milk (DIM).

After parturition, study animals were examined daily based on a pre-defined SOP for fresh cow monitoring, including measuring of rectal temperature, estimation of rumen fill, scoring of manure consistence (Zaaijer, 2001). Examination of the uterus and its contents by palpation per rectum and evaluation of vaginal discharge (Sheldon *et al.*, 2009) was conducted at 5 DIM and repeated at 8 DIM for cows with pathological discharge at 5 DIM. All examinations were performed by investigators of the Clinical Unit for Herd Health Management in Ruminants from the University of Veterinary Medicine Vienna, in cooperation with farm staff after the morning milking (06.00–08.00 am). During examinations and sampling procedures cows were fixed in headlocks.

Additionally, body condition was scored at drying off, approx. three weeks before the expected calving day (i.e. in the 'close up' pen) and at the day of parturition by visual observation (Edmonson *et al.*, 1989) and back fat measurement (Schröder & Staufenbiel, 2006) by use of an ultrasound device (BCF Easy-Scan, BCF Technology Ltd, Bellshill, Scotland). Blood samples were collected at drying off, while entering the close up pen, at parturition (D0) and on Days 3, 5 and 8 of lactation from a coccygeal vessel using vacuum tubes coated with a clot activator for serum collection (Vacuette, 9mL, Greiner Bio-One GmbH, Kremsmünster, Austria). Samples were centrifuged and serum was stored at -25 °C for further analyses. On the day of parturition, serum was tested on farm for total Ca concentration with the VetTest 8008 device (IDEXX, Westbrook, Maine, United States of America). For ketosis monitoring, the concentration of beta-hydroxybutyrate (BHB) was determined by use of a handheld device (FreeStyle Precision Xtra, Abbott GmbH and Co. KG, Wiesbaden, Germany).

Statistical analyses

For statistical analyses, data of animals suffering from health disorders were retrospectively matched with data of healthy control animals based on the date of parturition and parity. A healthy control animal had no pathological findings and/or diagnoses from 14 days before to 14 days after parturition and was only matched with a single diseased animal. Data were entered into Excel 2010 worksheets (Microsoft Corp., Redmond, WA, USA) and analyses were performed with the software package SPSS (version 24.0, IBM SPSS Inc., Munich, Germany). The duration of activity events were tested for normal distribution with the Kolmogorov-Smirnov test. To test for an association between the duration of activity events of healthy and diseases cows, the Mann-Whitney-U test was performed and Spearman´s rho (ρ) correlation coefficients were determined. The level of significance was set at $P < 0.05$ for all statistical analyses.

Results and discussion

So far, data of 156 animals suffering from health disorders and their 156 healthy controls are available. Considering the group of animals showing health disorders, 65 (42%) animals were diagnosed with one, 41 (26%) with two and 61 (39%) animals with equal or more than three disorders. Further information on the number of diagnoses is presented in Table 1.

Table 1. Diagnoses obtained in 156 animals suffering from health disorders

Abnormality / Diagnosis	Number of diagnoses	% of total diagnoses
Fever (≥ 39.5°C, single event)	120	35.8
Abnormal vaginal discharge on day five	70	20.9
Ketosis (BHB ≥ 1.2 mmol/L)	42	12.5
Indigestion	32	9.6
Retained placenta	26	7.8
Metritis	23	6.9
Diarrhea	6	1.8
Mastitis	6	1.8
Milk fever	4	1.2
Downer cow syndrome	4	1.2
Pneumonia	2	0.5
Total	**335**	**100.0**

The distribution of health disorders presented in Table 1 is comparable with the results of the studies conducted by Stangaferro *et al.* (2016a, b, c) on using rumination and activity data for identifying diseased cows.

As a preliminary result, Figure 1 shows the average rumination time per hour of animals suffering from health disorders compared with their corresponding controls from 14 days before to 14 days after parturition.

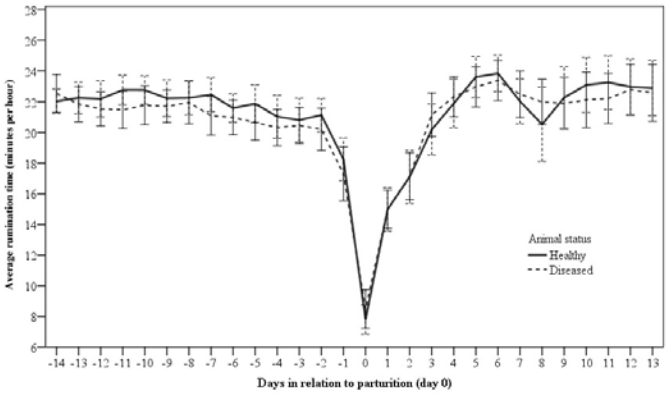

Figure 1. Average rumination time (min per hour) of animals suffering from health disorders compared with corresponding healthy cows in early lactation

Even if numerical differences in the average rumination time were observed between animals suffering from disorders and their healthy controls, significant differences were not detected. Further in-depth analyses of the SMARTBOW data considering combinations of the captured parameters are currently in progress. These results will be presented at the conference.

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References

Borchers, M.R., Chang. Y.M., Tsai, I.C., Wadsworth, B.A., and Bewley, J.M. (2016). A validation of technologies monitoring dairy cow feeding, ruminating, and lying behaviors. *Journal of Dairy Science,* 99: 7458–66.

Bewley, J. (2010). Precision Dairy Farming: Advanced analysis solutions for future profitability. In *The First North American Conference on Precision Dairy Management*. Toronto, Canada.

Cook, N., Oetzel, G., and Nordlund, K. (2006a). Modern techniques for monitoring high-producing dairy cows - 1. Principles of herd-level diagnoses. *In Practice,* 28: 510–515.

Cook, N., Oetzel, G., and Nordlund, K. (2006b). Modern techniques for monitoring high-producing dairy cows - 2. Practical applications. *In Practice*, 28: 598–603.

Edmonson, A.J., Lean, I.J., Weaver, L.D., Farver, T., and Webster, G. (1989). A body condition scoring chart for Holstein dairy cows. *Journal of Dairy Science,* 72: 68–78.

Fourichon, C., Seegers, H., Bareille, N., and Beaudeau, F. (1999). Effects of disease on milk production in the dairy cow: a review. *Preventive Veterinary Medicine,* 41: 1–35.

Ingvartsen, K.L. (2006). Feeding- and management-related diseases in the transition cow: Physiological adaptations around calving and strategies to reduce feeding-related diseases. *Animal Feed Science and Technology*, 126: 175–213.

Kaneene, J.B. and Scott Hurd, H. (1990). The national animal health monitoring system in Michigan. III. Cost estimates of selected dairy cattle diseases. *Preventive Veterinary Medicine,* 8: 127–140.

LeBlanc, S. (2006). Monitoring Programs for Transition Dairy Cows *Proceedings XXIV. World Buiatrics Congress*, Nice, France, 13.

Leblanc, S. (2010). Monitoring metabolic health of dairy cattle in the transition period. *Journal of Reproduction and Development*, 56: 29–35.

Lukas, J.M., Reneau, J.K., Wallace, R.L., and De Vries, A. (2015). A study of methods for evaluating the success of the transition period in early-lactation dairy cows. *Journal of Dairy Science,* 98: 250–262.

Rajala-Schultz, P.J., Grohn, Y.T., and McCulloch, C.E. (1999). Effects of milk fever, ketosis, and lameness on milk yield in dairy cows. *Journal of Dairy Science,* 82: 288–294.

Reiter, S., Sattlecker, G., Lidauer, L., Kickinger, F., Öhlschuster, M., Auer, W., Schweinzer, V., Klein-Jöbstl, D., Drillich, M., and Iwersen, M. (2018). Evaluation of an ear-tag-based accelerometer for monitoring rumination in dairy cows. *Journal of Dairy Science,* 101: 1–14.

Rutten, C.J., Velthuis, A.G.J., Steeneveld, W., and Hogeveen, H. (2013). Invited review: Sensors to support health management on dairy farms. *Journal of Dairy Science,* 96: 1928–1952.

Schröder, U.J. and Staufenbiel, R. (2006). Invited Review: Methods to determine body fat reserves in the dairy cow with special regard to ultrasonographic measurement of backfat thickness. *Journal of Dairy Science,* 89: 1–14.

Sheldon, I.M., Cronin, J., Goetze, L., Donofrio, G., and Schuberth, H.J. (2009). Defining postpartum uterine disease and the mechanisms of infection and immunity in the female reproductive tract in cattle. *Biology of Reproduction,* 81: 1025–1032.

Stangaferro, M.L., Wijma, R., Caixeta, L.S., Al-Abri, M.A., and Giordano, J.O. (2016a). Use of rumination and activity monitoring for the identification of dairy cows with health disorders: Part I. Metabolic and digestive disorders. *Journal of Dairy Science,* 99: 7395–7410.

Stangaferro, M.L., Wijma, R., Caixeta, L.S., Al-Abri, M.A., and Giordano, J.O. (2016b) Use of rumination and activity monitoring for the identification of dairy cows with health disorders: Part II. Mastitis. *Journal of Dairy Science*, 99: 7411–7421.

Stangaferro, M.L., Wijma, R., Caixeta, L.S., Al-Abri, M.A., and Giordano, J.O. (2016c) Use of rumination and activity monitoring for the identification of dairy cows with health disorders: Part III. Metritis. *Journal of Dairy Science,* 99: 7422–7433.

Vercouteren, M.M.A.A., Bittar, J.H.J., Pinedo, P.J., Risco, C.A., Santos, J.E.P., Vieira-Neto, A., and Galvão, K.N. (2015). Factors associated with early cyclicity in postpartum dairy cows. *Journal of Dairy Science,* 98: 229–239.

Wathes, C.M., Kristensen, H.H., Aerts, J.M., and Berckmans, D. (2008). Is precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall? *Computers and Electronics in Agriculture,* 64: 2–10.

Wolfger, B., Jones, B.W., Orsel, K. and Bewley, J.M. (2017). Technical note: Evaluation of an ear-attached real-time location monitoring system. *Journal of Dairy Science,* 100: 2219–2224.

Zaaijer, D. (2001). Fecal Scoring In: J. Hulsen, *Cow Signals: A practical guide for dairy farm management* Roodbont, NL, 56.

The use of GPS tracking and the LoRaWAN network to improve the productivity of grazing dairy cows: preliminary results

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Abstract

Current grazing systems used on commercial dairy farms in the UK are derived from New Zealand and Ireland and high yielding cows tend to under-perform. Previous work has shown that allocation of more than one grazing block per grazing bout can increase feed intakes and milk production. Bespoke LoRaWAN enabled collars with GPS and accelerometer sensors were developed. Accelerometer data (10 Hz) was calibrated to cow behaviour using 12 cows on four commercial farms, modelling the magnitude of the accelerometer vector on the cow eating activity (grazing or ruminating) using logistic regression ($P < 0.001$, accuracy = 95%) to give the probability of grazing. Collars were fitted to six cows on a commercial dairy unit for 18 weeks. GPS and summarised accelerometer data were collected every two minutes. Within a daily grazing bout positive changes in p(grazing) were accumulated and mapped against grazing activity. Once a threshold value for the accumulated positive changes in p(grazing) was exceeded, an elasticated 'bungee' gate was remotely triggered to give cows access to additional grazing. Drought conditions limited the preliminary trail to a one day-time grazing bout. Intakes were measured at 12 kg DM which is considerably higher than the typical industry figure of around 7 kg. Further work will develop the algorithms and the allocated grazing areas to assess if such gains in grass intake remain achievable on a wider range of commercial farms and with tighter control of the grazing residuals.

Keywords: dairy cattle grazing feed intakes

Introduction

In Britain the average milk yield of dairy cows has increased from 5,200–7,900 litres over the past two decades (AHDB, 2019). Current grazing systems used in the UK have been transferred from New Zealand and Ireland and are designed for lower yielding animals such that cows tend to under-perform at higher milk yields. To counter such under-performance cows are either buffer fed whilst at grass or housed through the summer period. Both strategies increase production costs and can lead to undesirable environmental and social effects. The work reported in this paper consists of results from a preliminary field trial that looked to increase grazed grass intakes through monitoring animal location and behaviour and allocating additional grazing accordingly.

Barrett *et al.* (2001) have shown that cows offered four separate grazing areas over a 24 h period have higher intakes (1.48 kg DM day^{-1}) than cows kept in a single paddock throughout. Dalley *et al.* (2001) allocated cows to one or six grazing blocks over a 24 h period. In the first two weeks of their trial the cows on multiple allocations gave more milk (1.8 l day^{-1}, $P < 0.001$). Over the full six weeks of the trial, the cows allocated the additional nutrients to reducing weight loss with significantly lower rates of weight loss (0.6 cf 1.2 kg body weight day^{-1}, $P < 0.05$). Commercial dairy farmers report increased feed intakes when they repeatedly 'push up' a Total Mixed Ration (TMR) at the feed face throughout the day. We have hypothesised that offering cows more than one block of grazing ground during the daytime grazing bout will trigger the cows to graze more leading to an increased feed intake.

Materials and methods

Bespoke LoRaWAN (2017) enabled collars fitted with GPS and accelerometer sensors were fitted to six cows on a commercial dairy farm in South England and left in place for 18 weeks. Accelerometer data were collected in three dimensions at 10 Hz from which was derived the magnitude of the acceleration vector. A GPS position fix was obtained every two minutes. Data were relayed to the cloud through the LoRaWAN network every two minutes to enable cow activity to be monitored in near real-time.

Calibration of accelerometer data to grazing activity.

In a separate trial 12 cows across four commercial farms were visually observed every two minutes over one grazing bout (6-7 hours) and eating activity (grazing or cudding) was recorded every two minutes. Where cows were undertaking the same activity at the start and end of the two minute window it was assumed they were involved in this activity throughout the two minute period and such data points were used in the calibration. The visual observations were compared to the magnitude of the acceleration vector to determine grazing activity (Figure 1).

The variance of the magnitudes over the two minute window was calculated and a logistic regression-based algorithm derived to predict feeding activity (grazing or ruminating) using the Minitab18. The derived binary logistic regression model predicted the probability of grazing (p(grazing)) ($P < 0.001$) with a predictive accuracy of 95% (specificity = 91%, sensitivity = 98%).

The pattern and duration of grazing and rumination were used to derive a cow-centred threshold to determine the timing for allocation of additional grazing using real-time field data as follows. For each of the six cows and at each data point the difference in predicted p(grazing) value was determined and positive values summed throughout the grazing bout. During an initial training period of three days the summed positive p(grazing) differences were compared to a plot of grazing activity and a numerical value was determined which represented when the animals started a secondary, low intensity grazing session part way through the grazing bout. When the system was deployed the summed positive p(grazing) differences were compared to the previously derived threshold value. When the threshold was exceeded for four cows a gate opening procedure was triggered.

The gate opening procedure triggered a LoRaWAN controlled gate opening actuator to release an elasticated 'bungee-gate' (seven meter width) to give the cows access to new grazing. During the daytime grazing bout, the cows were grazed in temporary paddocks defined with an electric fence within a larger permanently fenced field (Figure 2). Grazing and trial observations were not possible during the first part of the summer due to severe drought conditions.

Cows first grazed the field shown on 5 Sept and again on the trial day of 6 Sept. At this time the six cows fitted with LoRaWAN collars were part of a group of 58 cows with an average yield of 16.3 l day^{-1} and 239 days in milk. Grass cover (kg DM ha^{-1}) was measured before and after grazing each day using a rising plate meter and (AgHub F200, NZ with standard regression equation) and grazing areas (ha) from walking the allocated paddocks using an iPhone app (GPS Area Measure, Oceanic Software, 2015).

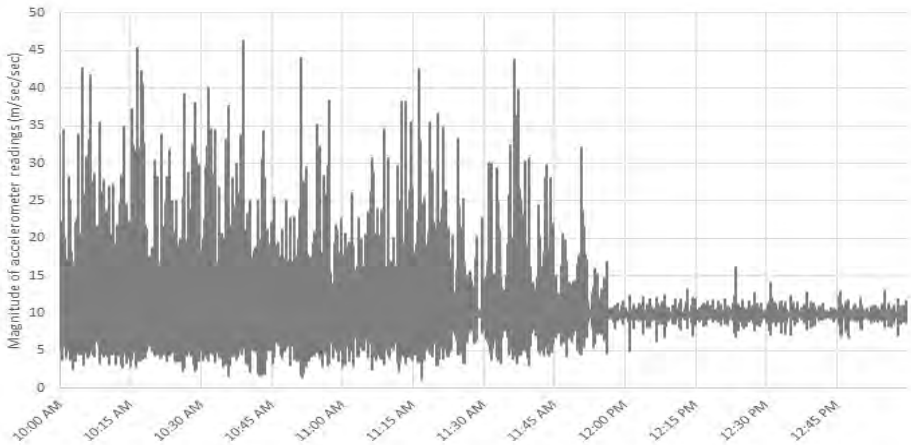

Figure 1. Magnitude of accelerometer data during a grazing and a rumination bout for a typical cow. Cow was visually observed to graze from 9:00–11:56 and then to ruminate until 13:00

Figure 2. Cow position in allocated grazing. Right-hand box defines initial grazing, left-hand box defines additional grazing. Grey line defines automatically opening 'bungee-gate', W – water trough. Shaded area is grazing allocation on 5 Sept, unshaded 6 Sept. Light grey symbols show average location of cows (n = 6) from start of grazing bout (07:30) to time when the 'bungee-gate' opened (12:00), darker grey symbols show average cow position from 12:00 to end of grazing bout at 14:30

Results and discussion

Total calculated intake per cow during the daytime grazing bout on 6 Sept was 12 kg DM of which 5.4 kg (45%) was consumed from the additional grazing areas.

The data loggers reported cow position for the full 18 weeks of the trial suggesting that a LoRaWAN based system can be used to collect data from grazing cows over a grazing season on a commercial farm. This overcomes the problems of short transmission ranges and limited battery life raised by Shalloo *et al.* (2018). Grazing behaviour can be determined from accelerometer data and, via a suitable algorithm, used to determine when a temporary 'bungee-gate' should be triggered to allow cows access to additional grazing. The initial results show an intake of 12 kg DM which is markedly greater than figures of 7-9 kg DM typically achieved on commercial farms (AHDB Dairy Grass+, 2011) and reported by Werner *et al.* (2019).

Table 1. Paddock areas, grass covers before and after grazing and calculated grass dry matter intakes

Grazing	Date	Area	Covers at 8:30am		Covers at 3:30pm		Eaten
		ha	kg DM ha^{-1}	kg DM	kg DM ha^{-1}	kg DM	kg DM
Initial	05-Sep	0.44	1,662	731	1,543	679	52
Additional	05-Sep	0.33	1,879	620	1,557	514	106
Initial	06-Sep	0.33	2,579	869	1,606	541	328
Additional	06-Sep	0.22	2,579	577	1,638	366	210
TOTALS		**1.32**		**2,797**		**2,100**	**697**

AHDB Grass+ (2011) recommends pasture covers at the start of grazing of 2,600–3,000 kg DM ha^{-1} and target residuals after grazing of 1,500 kg DM ha^{-1}. The initial covers in the grazing allocation of 6 Sept were within the target range (Table 1) but the residual covers were slightly higher than desired. Further work will be needed on adjusting the areas allocated for the initial and additional grazing blocks to ensure the target residual cover is achieved whilst maintaining the increased intakes.

References

AHDB Dairy Grass+ (2011). Accessed 18Feb19 https://dairy.ahdb.org.uk/resources-library/technical-information/grass-management/grassplus-section-4-planning-your-grazing.

AHDB (2019). Accessed 18Feb19 https://dairy.ahdb.org.uk/resources-library/market-information/farming-data/average-milk-yield.

Barrett, P.D., Laidlaw, A.S., Mayne, C.S. and Christie, H. (2001). Pattern of herbage intake rate and bite dimensions of rotationally grazed dairy cows as sward height declines. *Grass and Forage Science*, 56: 362–373.

Dalley, D.E., Roche, J.R., Moate, P.J. and Grainger, C. (2001). More frequent allocation of herbage does not improve the milk production in early lactation. *Australian Journal of Experimental Agriculture*, 41: 593–599.

LoRaWAN. (2017). LoRaWAN™ 1.1 Specification Accessed 5Nov18. https://lora-alliance.org/resource-hub/lorawantm-specification-v11

Minitab 18 Statistical Software (2017). [Computer software]. State College, PA: Minitab, Inc. (www.minitab.com)

Shalloo, L., O' Donovan, M., Leso, L., Werner, J., Ruelle, E., Geoghegan, A., O'Leary, N. (2018). Review: Grass-based dairy systems, data and precision technologies. *Animal,* 1–10. doi:10.1017/S175173111800246X.

Werner, J., Umstatter, C., Leso, L., Kennedy, E., Geoghegan, A., Shalloo, L., Schick, M., O'Brien, B. (2019). Evaluation and application potential of an accelerometer-based collar device for measuring grazing behaviour of dairy cows. *Animal.* Accessed 19Feb19. https://doi.org/10.1017/S1751731118003658 Published online: 08 February 2019.

Challenge of Precision Farm Management at Dairy Farms in North-East Germany

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Abstract

Cow comfort is a basic requirement for health and animal welfare of dairy cows. Farmers underestimate many factors, especially the installation of modern barn equipment is often neglected. In a research project an easy applicable solution was developed. 202 parameters have been collected in each of the 34 dairy farms. In this context we focused on the housing conditions and the associated management, using a precision livestock farming tool. The tool is also linked to other herd management systems and receives animal-related data from them. Through the objective and systematic collection of criteria and indicators in relation to behaviour, disposition and metabolism of dairy cows, a standardised root-cause analysis will identify weaknesses. With this software all mentioned parameters of each farm were recorded and these were compared with each other and processed, then the reference values were created. The system independently detects weak points of each animal and offers concrete solutions. The biggest weak points in the free stall barns are the insufficient dimensions of the cubicles, the barn hygiene and the bedding conditions. As a consequence of these weaknesses, the cows are enduring health problems. As an example, at 98% of the farms, more than 89% of the cows have lesions at the joints and more than 86% have major cleanliness problems at the back. Therefore, the farms regularly have to implement a self-monitoring system to improve the barn management. Using the results, uniform evidence-based recommendations for optimising the barn environment and management can be established.

Keywords: cow comfort, animal welfare, farm management, self-monitoring, precision dairy farming

Introduction

Cow comfort and animal welfare are important topics for the dairy industry (Barkema *et al.*, 2015). Cow longevity refers to how long the cow stays in the herd. The modern dairy cow has a short longevity, far below their biological potential (Alvåsen, 2018). Longevity is an important economic trait in dairy production. Increasing the productive lifetime of dairy production as cows must typically reach the second lactation to produce sufficient milk to break even on rearing costs. Furthermore, with increased longevity, the mean production of the herd could be higher because a large proportion of the culling decisions are based on production and because the proportion of mature cows, which generally produce more milk than young cows, would be increased (Alvåsen, 2018). To increase the longevity, the farmers have to observe the relation between the barn design and the welfare of the cow, because the term ´welfare´ refers to the state of an individual in relation to its environment and this can be measured. Both issues - failure to cope with the environment and difficulty in coping - are indicators of poor welfare. Suffering and poor welfare often emerge conjointly but welfare can be poor without suffering and welfare should not be defined solely in terms of subjective experiences (Broom, 1991). In order to avoid suffering at an early stage and to monitor animal health optimal, animal husbandry and industry are increasingly relying on precision livestock farming. Quantifying animal-based measures (e.g. prevalence of lameness and injuries, lying time and production information), evaluating environmental factors (e.g. barn design and stall

dimensions) and determining management practices (e.g. record keeping and management training) are proven methods of assessing animal welfare (Morabito *et al.,* 2017). The principal reasons of cow elimination are udder diseases, claws diseases and metabolic disorders of the cows. These are the most frequently used by the farmers. Major problems like fertility and claws diseases have specific reasons, like issues in the management and the barn design, which are not inspected and are unlisted in the herd management program.

Materials and methods

Study design and data collection

This study presents the results of one part from the project: 'Animal welfare and economic efficiency in the future-oriented dairy farming – an evaluation of various actions and their economic impact'. This study is intended to give an overview of the hygienic and technical condition of the barns in North East Germany, using a precision livestock farming tool. It reflects the modern form of digitisation in animal husbandry. For this study, the most important parameters were highlighted to illustrate the impact of management and barn design on animal health and welfare. The study took place on 34 dairy farms in North East Germany, especially in the three federal states: Mecklenburg-West Pomerania, Brandenburg and Schleswig-Holstein. 202 parameters have been collected in 54 barns of 34 dairy farms. The farms are assorted to the number of milking cows in four groups; group 1: up to 300 milking cows, group 2: 301–599 milking cows, group 3: 600–900 milking cows, group 4: over 900 milking cows. All farms, except one in Schleswig-Holstein with Angler breed and one in Mecklenburg-Vorpommern with Jersey breed, have Holstein-Friesian breed. All farms were analysed in the period of April to November 2017. The data collection was conducted three hours after feeding. In this present study, the cleanliness condition of the cows and the injuries at the joints are presented and the associated causes such as cubicle contamination, cubicle and barn management, inadequate cubicle dimensioning and the insufficient space available for the cows are explained. All these parameters were captured with the precision livestock tool ´Cows and More´. This tool is a development of an expert system with which it is possible, using animal and behavioural criteria, to discover weaknesses in husbandry and management in freestall dairy barns. With this software, all mentioned parameters for each farm were recorded and these were networked with each other and processed, so that the reference values were created. The digital root-cause analysis is based on a comparison of the individual farm with defined goals and comparison values of a specific dataset (Landwirtschaftskammer NRW, 2018). The recorded actual values were compared with the reference values and the limit values and then automatically evaluated in the system. Different evaluation schemes were used to assess the cleanliness of the cows and the injuries to the animals. A school grading system was used to assess the cleanliness of the cows. An average score of 2.7, which describes the baseline target value, should not be exceeded for any region. To describe the frequency of injury at the joints, all injuries at the respective detection points were summarised with reference to each detection group and stated in percent. The limit values for each injury range from 0–15% (Table 2). The individual limits should not be exceeded.

Statistical analysis

In each of the 54 barns, all specified values were collected in a special data entry group. Collectively, there are over 2,100 separate measuring values of all 34 farms for the housing conditions and the associated management at the farms.

Data were analysed by using the IBM SPSS Statistic 25 software package (IBM Deutschland GmbH, Ehningen, Germany). The descriptive statistics were analysed using the explorative data analysis. The graphs (Figure 1–4) were created by Excel 2016.

Results and discussion

Cleanliness and injuries at the joint by the cows

If you can detect weak points on the cows, these are signs of an inadequate husbandry environment. Table 1 shows the weak points of cleanliness at seven different body regions of the cow. In the body regions, tail, tail tassel, ischium and the lower legs, this limit value of 2.7 is strongly exceeded. These values are an average value of all 34 farms corresponding to 54 barns. In the individual barns, the measured values covered an extensive bandwidth, some farms had very clean animals, others had very dirty animals. These poorly cleanliness values act as an indicator for management weaknesses as well as inadequate barn and box dimensions.

Table 1. Cleanliness of the cows at the 34 farms

Measurement points at the cows	Average of the 54 barns	Target value
Hindquarters	2.79	2.7
Back	2.65	2.7
Udder / belly	2.59	2.7
Tail	3.25	2.7
Tail tassel	3.95	2.7
Ischium	3.19	2.7
Lower leg	3.17	2.7

Another major weakness in the evaluation of cows on the farms is the injuries to the joints of cows. Abnormalities to the joints always indicate weak points in the cubicles and in the running area. Table 2 shows the measurement points of the lesions at six different body regions. The evaluation differentiated the degree of injury, as shown in Table 2. Each body region is anatomically different and thus the body regions differ in their robustness. Thus, baseline target values range from 0–15%. The baseline target values for the degree of injury should not be exceeded. Ekman *et al.* (2018) state that hock lesions are a common problem in modern dairy production. The statement can only be agreed to. The present study is pointing in the same direction. Notable are the body regions like the tarsal joints, the spine, the withers and the carpal joints which show larger changes in all 54 barns. These values are averages of all 34 farms corresponding to 54 barns. In the individual barns the measured values covered an extensive bandwidth, some farms had very sick animals, others had very agile and healthy animals. These poorly injury values indicate big inadequate barn and box dimensions as well as management weaknesses.

Table 2. Lesions at the joints of the cows at the 34 farms

Measurement points at the cows	Average of the 54 barns in %	Target value in %
Tarsal joint hairless area	32.5	15
Tarsal joint skin free area	1.7	5
Tarsal joint swelling	4.2	5
Tarsal joint open swelling	0.5	0
Knee hairless area	5.2	5
Knee skin free area	1.0	0
Swelling spine	15.5	0
Open swelling spin	0.8	0
Hairless withers	18.9	5
Skin free withers	0.1	0
Swelling withers	4.5	0
Dewlap hairless patch	1.1	2
Carpal joint hairless area	16.8	15
Carpal joint skin free area	0.2	0
Carpal joint swelling	1.9	0

Hygiene of the most important functional areas

In a free-stall barn there are four functional areas which should be designed animal-friendly. The functional areas are the walking area, feeding area, resting area and the milking centre. The hygiene measures in these areas should be carried out very carefully and regularly. Tucker *et al.* (2003) agree with the description of the following study and the statement that the lying surface is known to affect dairy cows in several ways, including behaviour and leg, claws and udder health. Figure 1 shows the frequency of contamination in the cubicles. The graph shows all 53 barns and the corresponding contamination in boxes and the faeces placements. One of the 54 barns was excluded as it does not provide a free-stall barn for the animals. The baseline target value for normal soiling in the cubicles and thus completely acceptable is 10%. Figure 1 shows that in all 53 barns, contamination was found three hours after feeding. Only 21 barns had a total contamination in the cubicles below 10%. The factor of soiling of the box under the bracket is disturbing. 50 of 53 barns have lateral soiling in the cubicles. In contrast to centrally placed manure deposits which could be detected in 40 barns, this is a significant difference indicating problems in box dimensioning. In addition, there is a limit value for manure placement, which is 5%. This limit is exceeded in 37 barns for lateral soiling of the barns and in only 24 stalls for central manure deposits. These results only give an even greater indication that the box dimensions in the farms are not adequate.

Figure 2 shows a big management weakness in the cleanliness of the walking alley and the drinking trough. The cleanliness of the passes and the troughs is remarkable and may have unpleasant consequences for the cows. The walkways and passes are very slippery due to the constant soiling and humidity for the animals and by this high excrement-emergence in the walkways, it also comes to the stronger contamination at the tail, tail tassel and lower leg. Cows

have great difficulty walking on floors that are too smooth. In conjunction with excessively narrow passes, as can be seen in the surveyed farms, with a width of passes of 2.39 m, 2.32 m for the feeding course and 2.34 m for the way of the box, the animals slip heavily when walking and injuries occur at the protruding joints. In order to eliminate these weak points, farmers have to readjust the tool pre-setting of the steady slider and change their daily working routine.

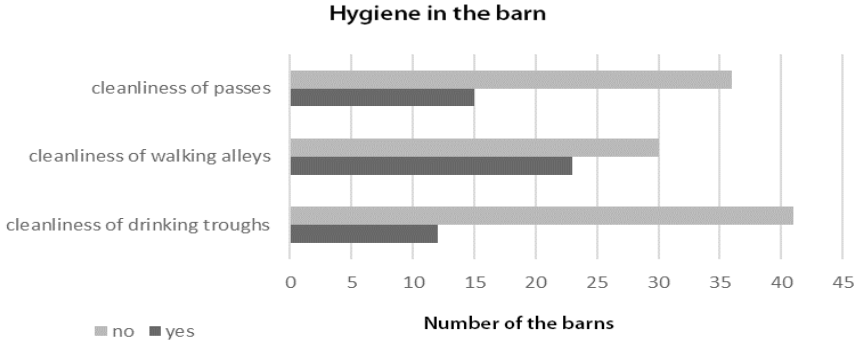

Figure 1. Cleanliness of the walking alleys and the drinking troughs as indicators of severe management weakness

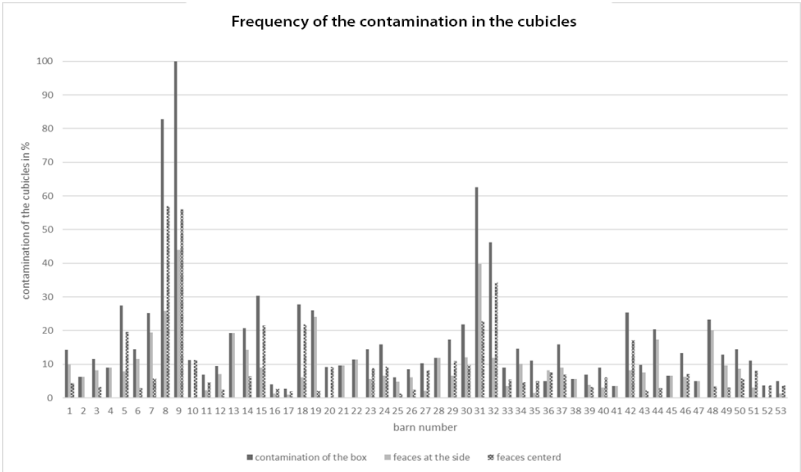

Figure 2. The frequency of contamination in the cubicles with different placements

Insufficient organic cover and hollow formation in the cubicles

A further management problem is the maintenance of the boxes in respect to the bedding. During the investigation we found three different cubicle types in the barns, the raised boxes, the low boxes and the higher deep boxes. 2,722 high bed cubicles, 2,685 low bed cubicles and 183 higher deep cubicles have been evaluated. Inadequate box coverage and high hollow formation in the low bed boxes have the effect of the cows being placed in the cubicles incorrectly, to swelling of the joints and even infections due to a lack of hygiene. Approximately 41.92% of all high bed cubicles (N = 2,722 boxes) indicated a solid organic cover under 50%. That means the cows only lie on a rubber mat and in the excrements. This results in abrasions and swellings primarily on the tarsal and carpal joints. Only 759 cubicles had an optimum solid organic cover. 63.95% of all low bed cubicles (N = 2,685) indicated intense hollows. This value is more than critical. The same fact is shown in the higher deep boxes.

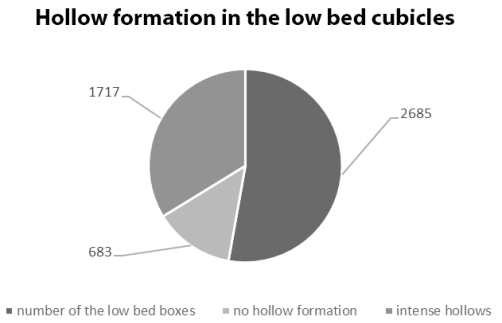

Figure 3. Hollow formation in the low bed cubicles

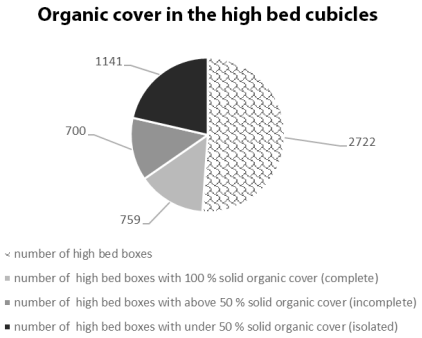

Figure 4. Organic cover in the high bed cubicles

Insufficient box dimensions

Due to the climate, cows in our latitudes spend at least half of the year in the barn. Even during grazing periods, cows come to the barn at least twice a day to be milked. The barn is therefore a central place for successful dairy farming (Hulsen, 2012). The barn is a complex system. The human being must translate the needs of the cow into building plans. The barn combines several issues, such as the barn equipment, the space available, the tread conditions and the management. If one of these points has a weakness, it has a major impact directly on the animal. Cows lie 10–14 hours a day. Hulsen (2012) is also of the opinion, that lying is important for many reasons, because the animal rests, the claws recover and can dry off, there is more space in the walking alleys and up to 30% more blood flows through the udder. The farmers build the barns according to the conditions of the subsidy law, without paying attention to the size and requirements of their animals. Table 3 shows these impacts which were found in almost every barn. Table 4 shows the large deviations of the cubicle and barn dimensions in comparison to the minimum requirements for the breed Deutsche Holsteins. The inadequate dimensions were found in newly built and old barns. The biggest problem in the barn construction can be found in the total length of the box, the width of the box and the neck tube height. Due to incorrect settings in the boxes, the weak points and impairments of the animal shown above occur. Also a result of the poor cubicle comfort is that the cows only lie down when they are really tired and then remain lying down too long. This makes the cows drink and eat less. Physical problems quickly arise, such as thick hocks.

The boxes that are too narrow and too short, lead to injuries at the spine (see point of injuries at the joints). The height of the neck brisket of 1.10 m is responsible for the hairless areas and swellings at the withers. The insufficient distance of neck bracket to the level of excrement and the length of the boxes are the reasons for the oblique lying in the cubicles and the resulting faeces at the side in the cubicles. These are the causes of the weak points of the cows listed above.

The additional overcapacities in the individual groups primarily lead to an inadequate animal/feeding place relation and sometimes also to a poor animal/cubicle place relation.

This relation, which is presented in Table 3, must be considered in a different way. Many cubicles cannot be used due to the dimensions and protruding parts or gates which cover the boxes.

Table 3. Animal - square conditions of all 54 barns

Animal-square conditions	Average of the 54 barns	Target value for animal-square conditions
Animal – cubicle relation	1,04:1	1:1
Animal – feeding fence relation	0,78:1	1:1

Table 4. Deviations of the cubicle and barn dimensions

Measurement points in the cubicles and the barn	Average of the 54 barns in cm	Target value in cm
Width of box	109	120
Distance neck bracket to level of excrement	14	165-175
Height of neck brisket	110	130-135
Intensity of faeces level	24	15-20
Height of brisket board	10	13
Length of the bed surface	181	180-195
Total length of wall box	219	260-280
Total length of (half) double box	175	240-260
Width of feeding course	332	400
Width of way of the box	234	300
Width of pass	239	250

Conclusions

The basic are the four pillars of stable building, the cow comfort, working efficiency, flexibility and expandability of the barn and durability, as well as cost effectiveness. Adapting these factors to the existing herd is not easy, as the present study shows.

It can be concluded that the hygiene management and the monitoring of the cubicles are the biggest problem in all the 34 farms analysed. The weak points of the box dimensioning as well as the box and barn hygiene and the resulting weak points of the cows' cleanliness and injuries at the joints at the cows, which are at the same time recognition parameters of the causes, should be checked and adapted regularly.

Finally, due to the identified weaknesses, a measure plan was developed. This shows how to adapt the boxes in the relevant farms and how to improve management in order to ensure animal welfare and integrate it into workaday routine. Self-monitoring is indispensable at the farms.

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References

Alvåsen, K., Dohoo, I., Roth, A., Emanuelson, U. (2018). Farm characteristics and management routines related to cow longevity: a survey among Swedish dairy farmers. *Acta Veterinaria Scandinavica,* 60: 38.

Broom, D.M. (1991). Animal Welfare: concepts and measurements. *Journal of Dairy Science*, 69: 4167–4175.

Barkema, H.W., von Keyserlingk, M.A.G., Kastelic, J.P., Lam, T.J.G.M., Luby, C. Roy, J.-P., LeBlanc, S.J., Keefe, G.P., Kelton, D.F. (2015). Changes in the dairy industry affecting dairy health and welfare. *Journal of Dairy Science*, 98: 7426–7445.

Ekman, L., Nyman, A.-K., Landin, H., Wller, K.P. (2018). Hock lesions in dairy cows in freestall herds: a cross-sectional study of prevalence and risk factors. Acta Veterinaria Scandinavica 60, 47.

Hulsen, J. (2010). *Bauen für die Kuh,* , RoodBont, Zupthen, Netherlands, 16 pp.

Hulsen, J. (2012). *Kuh-Signale – Krankheiten und Störungen früher erkennen*, RoodBont, Zupthen, Netherlands, 4 pp.

Hulsen, J. (2014). *Cow Signals Checkbook – Working on health, production and welfare,* RoodBont, Zupthen, Netherlands, 25 pp.

LAVES (2007). *Tierschutzleitlinie für die Milchkuhhaltung,* Niedersächsisches Ministerium für den ländlichen Raum, Ernährung, Landwirtschaft und Verbraucherschutz, Ref. 204, Hannover, Germany, 19–40.

Landwirtschaftskammmer Nordrhein-Westfalen (2018). *Cows and more – what the cows tell us…*, Bad Sassendorf, Germany.

Morabito, E., Barkema, H.W., Pajor, E.A., Solano, L., Pellerin, D., Orsel, K. (2017). Effects of changing freestall area on lameness, lying time, and leg injuries on dairy farms in Alberta, Canada. *Journal of Dairy Science,* 100: 6516–6526.

Ofner-Schröck, E., Breininger, W., Lenz, V. (2017). *Stallbau für die Rinderhaltung,* Leopold Stocker Verlag, Stuttgart, Germany, 6 pp.

Tucker, C.B., Weary, D.M. (2004). Bedding on Geotextile Mattresses: How much is Needed to Improve Cow Comfort?. *Journal of Dairy Science*, 87: 2889–2895.

Tucker, C.B., Weary, D.M., Fraser, D. (2003). Effects of Three Types of Free-Stall Surfaces on Preferences and Stall Usage by Dairy Cows. *Journal of Dairy Science*, 86: 521–529.

A combined method for cow individual feed intake monitoring

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Abstract

Monitoring individual cow feed intake is important for improving dairy farm efficiency. The cost, time and needed maintenance of off-the-shelf systems make them impractical for commercial farmers. We developed a system for measurement and estimation of the feed intake of all cows in a herd during all the lactation period with the goal to fit farmers' requirements. The feed intake was measured by a system consisting of four principal parts: (a) a hanging weighing system (simplified scales hanging on a single load cell), (b) a visual cow identification, (c) an automatic cleaning system, and (d) an algorithm for feed intake estimation based on a linear mixed effect model including milk yield and content, body mass, meal duration and frequency. The system was validated during a two-month experiment with six scales and 12 cows in a barn modelling a commercial one. The validation experiment showed that the system fulfilled the requirement: the three most inefficient cows were found by feed mass measuring. In an example of using the feed behaviour model two inefficient cows were correctly predicted. The scales were accurate within 50 g; the visual cow identification rate was greater than 96% and routine farm practices continued as usual, though with delay. The average cost for a feeding station was about $1,500. Thus, the system can potentially be used for ranking cows by their efficiency in commercial facilities.

Keywords: Individual feed intake monitoring, cow ranking, feed mass measurement accuracy, cow efficiency, cow feed behaviour model

Introduction

Cattle feed constitutes more than 60% of farm expenses (Ben Meir *et al.*, 2018). Identifying and replacing inefficient cows, and breeding more efficient cows, may improve the farm's financial situation (Halachmi *et al.*, 1998, Herd *et al.*, 2003). Existing feed intake measurement systems were designed primarily for research. These systems have complex structures and are also labour intensive, usually requiring individual bin feed distribution and cleaning. All of these factors make the existing systems impractical for commercial farmers. Hence, a less labour-intensive, less costly system designed for commercial farm settings should be developed.

Feed intake is typically measured by electronic scales (i.e. direct measurement of feed mass). Self-designed scales systems were reported by Halachmi *et al.* (1998), Bach *et al.* (2004) and Dahlke *et al.* (2008). Off-the-shelf commercial scale-based systems were used by Mendes *et al.* (2014), Chizzotti *et al.* (2015) and others. These systems consist of three main components: a feed container weighed by an electronic scale (usually with two to four load cells); a cow identification system (usually Radio-Frequency Identification (RFID)) including chips and antennae (Awad, 2016); and a mechanism to clean the feed containers, which is usually done manually.

To measure the feed intake, all the cows in a feeding lane must be recognised simultaneously. To replace a high-cost RFID antenna at each feeding station, we suggest using a lower cost method, utilising either visual or biometric identification, based on a Red-Green-Blue (RGB) camera (Andrew *et al.*, 2016).

To predict cow behaviour, particularly, feed intake, without actual measuring, mathematical models are used. Pastell *et al.* (2017) recognised feeding using hidden Markov chains. Faverdin *et al.* (2017) used long term and short term effects in the cow body weight dynamics. Halachmi *et al.* (2004) used mixed effect model built on large scale database. To improve the accuracy of a model, we used calibration of the models for specific cows by the feed behaviour measuring during a short period.

In this study, we developed a measurement system with the needs of commercial dairy farms in mind. We defined the following requirements for the system: 30% of the most inefficient cows must be found every year before selecting replacement cows; the system must be adapted to the farm practices: feed distribution, pushing, and residuals removal. The system functionality was similar to existing feed measurement systems on research farms, although it included the following improvements: simplified hanging scales with a single load cell; a cow identification system based on machine vision; an automatic feed cleaning system; and a cow behaviour model integrated in the system.

The hypothesis of this study was: the system developed can rank cows by efficiency.

The goal of this study was to develop and validate a new system to measure individual cow feed intake, which would enable dairy producers to rank cows by their efficiency under commercial conditions.

Material and methods

Mechanical Design

The scales consisted of a feed container hanging on a single load cell installed on a frame above the feeding area, as shown in Figure 1. The frame holding the front part of the container allowed passage of a feed distribution wagon. The dimensions of the feed container were 1 x 0.65 x 0.45 m. The container could hold up to 65 kg of feed.

The chain holding the feed container provided flexibility to the structure and made it possible to turn the container over. It is turned by a 6 m truss lifted by a three-phase motor (P0.37kW, Motovario) with a 1:50 gear (B50, Motovario). During the lifting, the feed remnants fell freely through the opening front door. The clearance between the lowest point of the lifted container and the floor was more than 0.5 m allowing the feeding lane below the containers to be cleaned by a feed pusher.

The cameras photographing the cow numbers were installed on arms placed four meters above the feeding area on the facility's structure (Figure 1). Plastic plates 48 x 46 mm with white numbers on red backgrounds (Lely, The Netherlands) were placed on the collars on each cow. To recognise the cows isolated for feed intake measurement, six digits (0, 2, 4, 5, 7, 9) were used. To increase the successful recognition rate, four identical digits were put on each collar to provide different angles of view when the plates were on both sides of the collar.

The scale used a 100 kg load cell with 50 g precision (L6G, Zemic Europe B.V.). The signal from the load cell was amplified by a load cell amplifier (HX711, SparkFun Electronics) and read by a microcontroller (Uno, Arduino). Three load cells were sampled by a single microcontroller connected by the serial protocol to a computer.

Two Internet Protocol (IP) cameras (5 MP, DS-2CD2652F-I, HikVision), connected through a switch to a computer, photographed the feeding area.

Figure 1. Side view of the feed intake measuring system: 1 – cow identification camera, 2 – cowshed structure, 3 – electronics box, 4 – load cell, 5 – feed container chain, 6 – lifting cable, 7 – frame, 8 – feed containers, 9 – lifting truss, 10 – the axis on which the feed container turns is located at the forward edge, 11 – front door opens during lifting

Cow feed behaviour model

The cow feed behaviour was modelled by a linear mixed model (LMM) (West *et al.*, 2007). The LMM formula was constructed by minimising the error in the feed intake prediction. The model includes the following parameters.

$$\text{DMI} \sim \text{MealDuration} + \text{MealNumber} + \text{MY} + \text{MilkProtein} + \text{BW} + \text{LactationDay} + \text{ratioBW\_MY} + (\text{MY} \mid \text{CowNo}), \quad (1)$$

where DMI is dry matter intake, MealDuration is total day feeding duration, MealNumber is total day number of meals, MY is milk yield, MilkProtein is average milk protein percentage in a day milk yield, BW is average day cow body weight, LactationDay is day in lactation, ratio BW_MY is average day ratio BW/MY and CowNo is cow ID number.

The model (defined here as "general model") was created based on the data for 76 Holstein Israeli cows achieved from 2016 until 2018 in the research cowshed in the ARO (Volcani centre) described by Halachmi *et al.* (2004). For each cow the data were recorded for 53 up to 267 days in average 141 days, total information from 10,950 cow-days.

Experiment

A prototype was installed on a research farm at the Volcani ARO in a commercial-like barn. A part of a facility including six stations located between two facility columns was separated. Two groups of six randomly chosen Holstein cows in each group participated in the experiment, which lasted 30 days for each group. The following criteria were tested in the experiment.

The scale accuracy in measuring a single meal was tested by comparing the mass achieved automatically using the feeding stalls, with a measurement of mass performed manually, using a reference scale with 10 gr accuracy. The manual measurements were conducted before and after cow meals for each feeding stall. This was done 15 times daily, at random times during the day, over a period of ten days (150 total samplings).

Recognising the feedings and measuring their duration were validated manually by comparing with images collected by the cameras during 10 days each 5 s. The cow identification success rate was validated similarly. To estimate the accuracy, the slope and P-value of the regression between the data achieved by the system and the reference was calculated using MATLAB (MathWorks).

The convenience of the feed measurement system was analysed according to the ability to perform the routine farm practices that the system entails and the time necessary to do so.

In order to rank the individual cows by their efficiency, feed efficiency was defined as the ratio between the dry matter intake (DMI) and the mass of the milk yield (MY): efficiency = DMI/MY. The daily MY was measured by the AfiMilk (Afikim, Israel) system during milking (accurate to 3%). The overall efficiency during the experiment period was calculated as the sum of the MY divided by the sum of the DMI for the entire period. To model a realistic case, when 30% of cows are chosen for replacement from a herd of 100–150 cows, we aimed to find the three most inefficient cows from the experimental group of 12 cows.

To estimate the influence of the accuracy of the feed measurement on the cow ranking, we compared the achieved ranking with two extreme cases: the standard error of the estimate was added and subtracted from each feed mass measurement.

An example of the ranking prediction by the feed behaviour model was shown. The collected data was separated into two parts: modelling part, consisting of the data collected during the first two weeks (which was sufficient for the successful prediction, Ben Meir *et al.*, 2018), was used for modelling and the validation part, consisting of data collected during the rest of the experiment, was used for validation of feed intake prediction and the cow ranking. The model was tested in three conditions, representing three possible configurations of the feed measuring system. (a) The modelling part of the collected data was not used, and the prediction was performed only based on the general model (simulating usage of the general model without need of the feed scales). (b) The general model was not used, and the prediction was performed only based on the model created from the modelling part (simulating absence of the general model and usage only of information achieved by the measuring system). (c) The modelling part was added to the general model (simulating current system configuration).

Results and discussion

The slope of the regression between the meal mass measured automatically by the system scales and the meal mass measured manually using the reference scale was 1.01 (P = 0.002). The standard error of the estimate was 50 g for a feeding and assumed as the accuracy of the system. This value is higher than that of the commercial systems (10 g for GrowSafe) and similar to that of self-designed systems (100 g for a system built by Halachmi *et al.*, 1998). Nevertheless, in this study we found that this accuracy was sufficient to compare cow efficiencies and recognise extremely inefficient cows.

The primary cause of measurement error was the mechanical structure of the scale, with the feed container hanging on a load cell. The flexibility enabled the cows to move and rotate the containers, and apply overload on the load cells, changing the transducing coefficient. To reduce this effect, improvements need to be made in the way in which the containers are attached to the load cells.

During the cow recognition experiment, 2,235 cow visits were registered manually and 2,154 automatically by the system. The automatic system missed 81 visits that were registered manually, resulting in 96.3% sensitivity. The system detected 54 false visits, resulting in 97.5% specificity. The slope of the regression between the feeding duration

measured automatically by the system and feeding duration measured manually from the videos was 0.965 (P = 0.0003). The sensitivity and specificity were lower than in previous studies (Bach *et al.*, 2004; 99.6% and 98.8%).

During the 2,154 visits registered by the system, the cow numbers were successfully recognised in 96.4% cases. This rate was lower than the rate provided by RFID (98.8% at Bach *et al.*, 2004). Despite the worth accuracy, the advantage of the proposed system is using cameras only, without additional devices (photocells in each feeding station); the identification rate can be increased further by using machine learning without auxiliary equipment, such as collars with numbers.

The convenience for the farm practices was estimated by the number of required actions and the time it took for each one, as presented in 0. The time was measured for six feeding stations of the feed measurement system and a six-meter-long feeding lane in a standard facility. The times listed in the table are the average of measurements made during five observations.

Table 1. Comparison of the average (±STD) time required for standard cowshed practices with and without the feed measuring system

Action	Without		With	
	Time	Required actions	Time	Required actions
Cleaning feed remnants from containers	5(±1)s	Pushing by pusher	23(±2.4)s	Lifting and lowering feed containers by operator
			4(±3.2)s	Visual observation by operator
			11(±4.2)s	Pushing by pusher
Feed distribution	13(±2.8)s	Driving the distribution wagon	26(±8.1)s	Driving the distribution wagon with special care
Feed pushing	3(±0.5)s	Pushing by pusher		
Total	21s		64s	

The main goals of the mechanical design of the feed measurement system were adapting it to existing farm infrastructure and routines and to minimise human intervention during the cleaning process. Unlike other reviewed feed measurement systems, the container of the designed system does not stand on the floor. This makes system maintenance easier relative to a system standing on the floor. That, in turn, simplifies the feed cleaning process by using machinery already used on farms, such as feed alley scrapers and tractors, or skid steers with attachments. In addition, the containers can be cleaned automatically by turning over, in contrast to the reviewed measurement systems, which require manual cleaning inside and around the containers.

The overall efficiency during the experiment for all cows is presented in Figure 2. The error bars represent extreme deviation of the scale accuracy added to each feeding. According to the overlapping of the error bars, the most inefficient cows are 3,227; 3;540 and 3633. The three most efficient cows are the cows 3,516; 3,597 and 3,610.

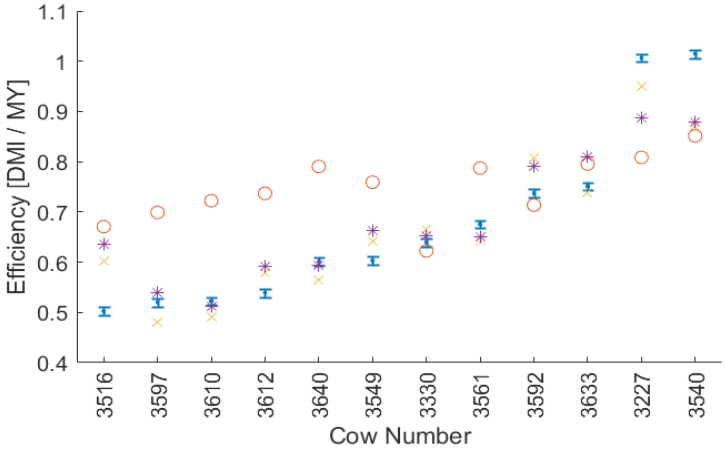

Figure 2. Efficiency (DMI/MY) of the cows participated in experiment. Dots with error bar represent the measured efficiency, o represent predicted efficiency based on the model in configuration (a), x – configuration (b) and * – configuration (c)

The cows ranking based on the feed mass measured by scales and example of the rank prediction by different configuration of the feed behaviour model is presented in 0. Assuming the measured efficiency as a reference, the general model with addition of the measured model (configuration (c)) yields the best result with one false recognised inefficient cow marked by bold (4) and without false detection for the maximal efficiency. Nevertheless, to validate the model in commercial conditions, additional experiment with larger number of cows is required.

Table 2. Ranking of the cows based on measuring the feed intake by scales, representing a reference for the model, and different configurations of the model. The false detected cows related to groups of three with the maximal and minimal efficiency are marked by bold

Measured	1	2	3	4	5	6	7	8	9	10	11	12
Conf. (a)	**7**	1	2	9	3	4	6	8	5	10	11	12
Conf. (b)	2	3	**5**	4	1	6	8	7	10	**9**	12	11
Conf. (c)	3	2	**4**	5	1	8	7	6	9	10	12	11

A simplified case of cow ranking was presented in the paper to illustrate the efficacy of the feed intake measurement system. Practically, to perform a comparison between cow efficiency, a number of parameters should be considered (DMI, milk content, etc.). Additionally, to use this system for the entire herd, information about feed consumption of each cow must be measured, which can be accomplished by two weeks periods for each cow (Ben Meir *et al.*, 2018). To apply the mode during the entire lactation period, the feed behaviour (feeding length and frequency) is currently measured by collar tags with accelerometers (SCR, Nataniya, Israel).

The major elements contributing to the cost of the system (about $1,500) were the quality of the load cells and cameras, and the complexity of the parts. In future studies, further cost reductions can be achieved by more robust algorithms for cow identification, requiring

fewer and/or lower quality cameras, changing the materials used or production methods of the feeding containers, etc.

Conclusions

The system described can be used to monitor individual cow feed intake due to its features, which are adapted to the needs of commercial farms. Despite the limited accuracy in the feed weight measurement and the cow recognition, the advantage of the system is in its simplicity, which provides sufficient accuracy for commercial needs. During the experiment, decisions about farm management were made based on the system's measurements, which potentially with the help of the feed behaviour model can be generalised for the entire barn during the lactation period.

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References

Andrew, W., Hannuna, S., Campbell, N., and Burghardt, T. (2016). Automatic individual Holstein Friesian cattle identification via selective local coat pattern matching in rgb-d imagery. In: *Proc. ICIP: IEEE International Conference on Image Processing* Phoenix, AZ, USA, 484–488.

Awad, A.I. (2016). From classical methods to animal biometrics: A review on cattle identification and tracking. *Computers and Electronics in Agriculture,* 123: 423–435.

Bach, A., Iglesias, C. and Busto, I. (2004). Technical Note: A Computerized System for Monitoring Feeding Behavior and Individual Feed Intake of Dairy Cattle. *Journal of Dairy Science,* 87(12): 4207–4209.

Ben Meir, Y.A., Nikbachat, M., Fortnik, Y., Jacoby, S., Levit, H., Adin, G., Cohen Zinder, M., Shabtay, A., Gershon, E., Zachut, M., Mabjeesh, S.J., Halachmi, I. and Miron, J. (2018). Eating behavior, milk production, rumination, and digestibility characteristics of high- and low-efficiency lactating cows fed a low-roughage diet. *Journal of Dairy Science,* 101(12): 10973–10984.

Chizzotti, M., Valente, E.E.L., Machado, F.S. and Pereira, L.G.R. (2015). Technical note: Validation of a system for monitoring individual feeding behavior and individual feed intake in dairy cattle. *Journal of Dairy Science*, 98(5): 3438–3442.

Dahlke, G., Strohbehn, D.R., Ingle, C. and Beedle, P. (2008). A Feed Intake Monitoring System for Cattle. *Animal Industry Report* AS 654, ASL R2279.

Halachmi, I., Edan, Y., Maltz, E., Peiper, U.M., Moallem, U. and Brukental, I. (1998). A Real-time Control System for Individual Dairy Cow Food Intake. *Computers and Electronics in Agriculture,* 20(2): 131–144.

Halachmi, I., Edan, Y., Moallem, U. and Maltz, E. (2004). Predicting Feed Intake of the Individual Dairy Cow. *Journal of Dairy Science,* 87(7): 2254–2267.

Herd, R.M., Archer, J.A. and Arthur, P.F. (2003). Reducing the Cost of Beef Production Through Genetic Improvement in Residual Feed Intake: Opportunity and Challenges to Application. *Journal of Animal Science,* 81: 9–17.

Faverdin, P., Charrier, A. and Fischer, A. (2017). Prediction of dry matter intake of lactating dairy cows with daily live weight and milk production measurements. In: *Proc. ECPLF: 8th European Conference on Precision Livestock Farming* Nantes, France, 35–44.

Mendes, E.D.M., Carstens, G.E., Tedeschi, L.O., Pinchak, W.E. and Friend, T.H. (2014). Validation of a System for Monitoring Feeding Behavior in Beef Cattle. *Journal of Animal Science*, 89: 2904–2910.

Pastell, M. and Frondelius, L. (2018). A hidden Markov model to estimate the time dairy cows spend in feeder based on indoor positioning data. *Computers and Electronics in Agriculture,* 152: 182–185.

Associating body condition score and parity with sub-optimal mobility in pasture-based dairy cows

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Abstract

Sub-optimal mobility in dairy cows can be broadly defined as abnormal gait which causes a deviation from the optimal walking pattern of a cow. Sub-optimal mobility is also associated with significant economic and environmental consequences, which have yet to be extensively researched or quantified in pasture-based systems. However, to quantify sub-optimal mobility in terms of its impacts economically and environmentally, and indeed to aid in the development of automated detection sensors for sub-optimal mobility, a clear understanding of the characteristics of a cow with sub-optimal mobility is required. So far, automated detection sensors have been successful for detecting moderate to severe forms of sub-optimal mobility. However, there is a need for a better understanding of the cow-level traits associated with all forms of sub-optimal mobility, including mild forms, to incorporate this into future development of automated detection sensors for sub-optimal mobility. Therefore, the aim of our study was to determine the associations between hoof disorders (both type and presence), body condition score, and all levels of sub-optimal mobility in pasture-based dairy cows using data from a large sample of Irish dairy farms. Mobility scores, body condition scores (BCS), claw disorder (presence and severity), and parity records were available for 6,927 dairy cows from 52 pasture-based herds. Binomial logistic regression analysis was completed to determine the associations between claw disorder (presence and severity), BCS, parity and sub-optimal mobility. The output variable was sub-optimal mobility (mobility score ≥ 1) and the predictor variables were specific claw disorders and their severities, BCS, and parity. Our results indicate that all severities of claw disorders, low BCS, and higher parity cows are all associated with an increased risk for sub-optimal mobility.

Keywords: lameness, claw disorder, body condition, parity, grass-based system

Introduction

Sub-optimal mobility is often overlooked in pasture-based systems, due to a perception that dairy cow mobility issues are far more prevalent in non-pasture-based systems (Somers and O'Grady, 2015). However, the incidence of mobility issues has been shown to be quite similar in both pasture and non-pasture based systems (Olmos *et al.*, 2009).

Many studies have already demonstrated the usefulness of automated detection sensors for sub-optimal mobility. However, more often than not, cows must already be severely sub-optimally mobile in order to be detected using such sensors (Mottram, 2015). In order for automated detection sensors to be capable of detecting cows with mild to moderate sub-optimal mobility, a clear understanding of a cows optimal gait is required (described in detail by (Van Nuffel *et al.*, 2015)). As well as this, cow-level traits associated with sub-optimal mobility need to be investigated and taken into consideration when developing such automated detection sensors for sub-optimal mobility. Although it is well known that claw disorders are the most important risk factors for the majority of cases of severe sub-optimal

mobility (Murray *et al.,* 1996), less is known about the association with mild and moderate forms of claw disorders and sub-optimal mobility. Throughout the literature, studies that do address the association between various cow characteristics and mobility issues mainly focus on the term lameness. However, lameness is a multifactorial term which is very difficult to definitively define (even among experts throughout the field (Green *et al.,* 2002), and more often than not refers to quite severe forms of sub-optimal mobility or 'clinical lameness'. Therefore, in this study we use the term optimal and sub-optimal mobility.

The focus of our study is to gain a better understanding of the quality of dairy cow mobility and the main factors associated with sub-optimal mobility in pasture-based dairy cows, using cow-level attributes. Therefore, besides understanding the association between claw disorders and mobility scores, we will also investigate the association between dairy cow body condition score (BCS), and parity, and sub-optimal mobility (Lim *et al.,* 2015). We define sub-optimal mobility in our study as 'any abnormality to a cow's gait which causes a deviation from the optimal walking pattern of a cow'. Thus, the severity of sub-optimal mobility can vary greatly, from slight deviations from optimal gait to severe immobility causing difficulty when walking (Beusker, 2007). Therefore, the objective of our study was to characterise sub-optimal mobility by determining their association with cow-level attributes, including: the presence, type and severity of claw disorders, BCS and cow parity.

Materials and methods

Cow Data

An Irish Department of Agriculture Food and the Marine funded study across spring calving dairy herds with the objective of collecting animal health data was used as the data source. Complete records for mobility score, claw disorders, BCS, and parity were available for 6,927 cows from 52 of the herds, and thus only these cows were included in our analysis. Average herd size was 163 cows and standard deviation was equal to 111. All the farms were operating a spring-calving pasture-based system, whereby over 70% of cows calve between January and March (Irish Cattle Breeding Statistics, 2018).

Mobility Score, Claw Disorders and BCS data

Each cow's mobility score and BCS were recorded by two trained technicians from Teagasc, Moorepark. Cows were mobility scored using the UK Agriculture and Horticulture Development Board four point scale, (https://dairy.ahdb.org.uk/technical-information/animal-health-welfare/lameness/husbandry-prevention/mobility-scoring/#.WXnhULuFOr8) during the 2015 calendar year. The BCS of every cow was assessed using both visual and tactile appraisal on a scale of 1–5 with 0.25 increments, as described by Edmonson *et al.* (1989). On a separate herd visit, each cow's hind legs were lifted for identification and scoring of claw disorders by claw-trimming professionals from one commercial company (Farm Relief Services (FRS), Roscrea, Co. Tipperary, Ireland. The claw disorders were identified using the claw atlas of the International Committee for Animal Recording (ICAR), 2015. Two types of claw disorders were recorded by the assessors: 1) non-infectious (overgrown claw, whiteline disease, hemorrhage, and sole ulcer) and 2) infectious type claw disorders (digital dermatitis). Overgrown claw, sole hemorrhage, and whiteline disease were each severity scored using a scale (0 through 3), whereby 0 = not affected, 1= mildly affected, 2= moderately affected, and 3 = severely affected. Sole ulcer and digital dermatitis were scored as binary traits (i.e. 0 = not affected or 1 = affected).

Statistical analysis

The associations between the predictor variables (BCS, specific claw disorders (presence and severity score), and cow parity) on mobility score (outcome variable) were assessed using a forward stepwise regression approach. Binomial logistic regression was used to

model nominal outcome variables, in which the log odds of the outcomes are modelled as a linear combination of the predictor variables. The outcome variable was mobility score (a categorical variable, grouped as optimal mobility (mobility score = 0) or sub-optimal mobility (mobility score ≥ 1)). The predictor variables were BCS (a categorical variable, put into three groups, which are: BCS < 3.00, BCS = 3.00, and BCS > 3, the presence and severity of each claw disorder, and cow parity 1, 2, or ≥ 3.

In the regression analysis, mobility score ≥ 1 was compared to a reference category (mobility score 0). For the predictor variables (claw disorder presence and severity, BCS, and cow parity) an odds ratio >1 indicates that an increase in the predictor variables increases the risk of occurrence of a specific category rather than the occurrence of the reference category, whereas an odds ratio < 1 indicates than an increase in the predictor variable decreases the risk of occurrence of a specific category rather than the occurrence of the reference category. Predicted probabilities for mobility score were used to assess model fit by visual comparison with observed data (Gelman *et al.,* 1996). Analyses were performed using the R statistical software (R Development Core Team, 2009; function 'glm' for binomial logistic regressions).

Results and discussion

In this study mobility score = 0 refers to a cow with optimal mobility, thus shows no signs of deviation from the optimal walking pattern as described by Van Nuffel *et al.* (2015). Therefore, mobility score ≥ 1 (mobility score 1, 2, and 3) refers to a cow with varying degrees of sub-optimal mobility, showing different levels of deviation from the optimal walking pattern of a cow, ranging from quite mild to very severe forms of sub-optimal mobility. Of all the cows, 2,641 had sub-optimal mobility (mobility score ≥ 1), while the remaining 4,286 cows had optimal mobility (mobility score = 0). For the cows with sub-optimal mobility, 58% had some form of an overgrown claw, 57% had some form of sole hemorrhage, 57% had some form of whiteline disease, 2.5% had some of sole ulcer, and 5% had some form of digital dermatitis.

The results of our study found that all forms of overgrown claw, sole hemorrhage, and whiteline disease have odds ratios greater than 1 (Table 1). These results indicate that all forms of overgrown claw, sole hemorrhage, and whiteline disease (mild, moderate and severe) increase the risk of occurrence of sub-optimal mobility (mobility score ≥ 0) rather than the reference category; optimal mobility (mobility score = 0). Even mild types of these claw disorders did increase the risk of occurrence of sub-optimal mobility rather than optimal mobility.

Similarly, for the binary scored claw disorders, all severities of both sole ulcer and digital dermatitis were also associated with an increased risk of occurrence of sub-optimal mobility. It is important to note the limitation of these results whereby cow's mobility score and BCS were recorded on the same day, while claw disorders and their severity scores were recorded on a separate farm visit, simply due to time restrictions.

The odds ratios for BCS were consistently < 1 (Table 1) indicating that cows with a high BCS (BCS = 3.00 and BCS > 3.00) are associated with a decreased risk of occurrence of sub-optimal mobility, compared to cows with a BCS < 3. Cow parity was also included in the model as a predictor variable for mobility. The odds ratios for cow parity were > 1 (Table 1) indicating that (1) parity 2 and ≥ 3 cows are associated with an increased risk of the occurrence of sub-optimal mobility, rather than the reference category; optimal mobility (compared to parity 1 cows).

Table 1. Odds ratios and 95% confidence interval for the binomial logistic regression model used to predict sub-optimal mobility (n = 6,927) by each claw disorder and body condition score

Risk factor	Reference value MS0	
	Odds ratio	
	MS ≥ 1	95% CI
Overgrown claw 1	1.19**	(1.08-1.31)
Overgrown claw 2	1.59***	(1.39-1.82)
Overgrown claw 3	4.63***	(3.45-6.30)
Sole hemorrhage 1	1.23***	(1.11-1.35)
Sole hemorrhage 2	1.36***	(1.19-1.56)
Sole hemorrhage 3	1.62***	(1.35-1.95)
Whiteline disease 1	1.17*	(1.05-1.29)
Whiteline disease 2	1.38***	(1.19-1.60)
Whiteline disease 3	1.95***	(1.65-2.32)
Sole ulcer 1	3.19***	(1.98-5.32)
Digital dermatitis 1	2.81***	(2.13-3.74)
Parity 2	1.46***	(1.28-1.67)
Parity ≥ 3	2.79***	(2.30-2.89)
BCS = 3	0.67***	(0.61-0.74)
BCS > 3	0.56***	(0.50-0.63)

MS = mobility score; CI = confidence interval
***, **, *, † odds ratio is significantly or tends to be different from 1 (P < 0.001, 0.01, 0.05, 0.10)

Conclusions

From the findings of this study, we conclude that there is an association between claw disorders (including both type and severity) and mild, moderate and severe forms of sub-optimal mobility in dairy cows in pasture-based systems, as well as an association between BCS, cow parity and sub-optimal mobility. Mild, moderate, and severely severity scored claw disorders, such as overgrown claw, sole hemorrhage, and whiteline disease all increased the risk of occurrence of mobility score ≥ 1 versus mobility score 0, whereby low BCS, as well as an higher cow parity were also associated with sub-optimal mobility score versus optimal mobility score. From this, mobility scoring can be used to identify problem cows, i.e. cows with mild forms of claw disorders, relatively earlier. There is also potential for technology to be developed in order to accurately measure mobility score of pasture-based dairy cows, while keeping in mind the associated cow level traits with sub-optimal mobility.

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References

Beusker, N. (2007). Welfare of dairy cows: Lameness in cattle. Literature review. in The institute of Animal Hygiene, Animal Welfare and Animal Ethology, School of Veterinary Medicine. Hannover, Germany.

Edmonson, A.J., I.J. Lean, L.D. Weaver, T. Farver, and G. Webster. (1989). A body condition scoring chart for holstein dairy cows. *Journal of Dairy Science,* 72: 68–78.

Gelman, A., X.-L. Meng, and H. Stern. (1996). Postierior predictive assessment of model fitness via realized discrepancies. *Statistica Sinica*, 6:733–760.

Green, L.E., V.J. Hedges, Y.H. Schukken, R.W. Blowey, and A.J. Packington. (2002). The impact of clinical lameness on the milk yield of dairy cows. *Journal of Dairy Science,* 85: 2250–2256.

Irish Cattle Breeding Statistics. (2018). Calving report statistics, dairy calving statistics 2008–2018. Irish Cattle Breeding Federation, Highfield House, Shinagh, Bandon, Co. Cork, Ireland. Portal at https://www.icbf.com/wp/wp-content/uploads/2018/09/Dairy-Calving-Stats-2018–1.pdf.

International committee for animal recording (ICAR). 2015.

Lim, P.Y., J.N. Huxley, J.A. Willshire, M.J. Green, A.R. Othman, and J. Kaler. (2015). Unravelling the temporal association between lameness and body condition score in dairy cattle using a multistate modelling approach. *Preventive Veterinary Medicine,* 118: 370–377.

Murray, R., D. Downham, M. Clarkson, W. Faull, J. Hughes, F. Manson, J. Merritt, W. Russell, J. Sutherst, and W. Ward. (1996). Epidemiology of lameness in dairy cattle: Description and analysis of foot lesions. *The Veterinary Record*, 138: 586–591.

Olmos, G., L. Boyle, A. Hanlon, J. Patton, J.J. Murphy, and J.F. Mee. (2009). Hoof disorders, locomotion ability and lying times of cubicle-housed compared to pasture-based dairy cows. *Livestock Science,* 125: 199–207.

Somers, J. and L. O'Grady. (2015). Foot lesions in lame cows on 10 dairy farms in ireland. *Irish Veterinary Journal,* 68: 10.

Statistics, I.C.B. (2018). Calving report statistics, dairy calving statistics 2008–2018. Highfield House, Shinagh, Bandon, Co. Cork, Ireland.

Van Nuffel, A., I. Zwertvaegher, L. Pluym, S. Van Weyenberg, V.M. Thorup, M. Pastell, B. Sonck, and W. Saeys. (2015). Lameness detection in dairy cows: Part 1. How to distinguish between non-lame and lame cows based on differences in locomotion or behavior. *Animal,* 5: 838–860.

The effect of grazing season length and stocking rate on milk production and supplementary feed requirements within spring calving dairy systems in the north-east of Ireland

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Abstract

Increasing the proportion of grass in the diet of the dairy cow is one of the fundamental objectives of Irish milk production systems. Significant potential exists to increase productivity from pasture by increasing stocking rate and extending grazing season length on dairy farms in the north-east region of Ireland. The objective of the experiment was to quantify the effect of grazing season (GS) length and stocking rate (SR) on milk production and supplementary feed requirements within an intensive spring calving system. In 2017, 120 spring calving dairy cows were randomly assigned pre-calving based on breed, parity, calving date and previous lactation milk yield to one of four grazing systems comprised of two grazing season (GS) lengths: average (AGS; 205 days; 15 March to 20 October) and extended (EGS; 270 days, 15 February to 20 November) and two SR treatments: medium (MSR; 2.5 cows/ha) and high (HSR; 2.9 cows/ha). Neither SR nor GS had a significant effect on individual animal performance in terms of milk yield, milk composition, average BW or average BCS. Higher SR resulted in significantly increased milk and milk fat plus protein production per hectare. As the AGS treatment was indoors for an additional 60 days between February and November, significantly more concentrate and silage were required during lactation compared with the EGS treatment.

Introduction

Temperate grazing systems are characterised by seasonal calving, a prolonged grazing season (> 275 days) and a primarily pasture diet (Dillon *et al.,* 2005). Such systems, based on a cheap feed source, provide pasture based milk producers with a competitive economic advantage over other production systems based on high milk output per hectare with reduced fixed and variable costs (Finneran *et al.,* 2010). It is also widely acknowledged that grass utilisation per hectare is the most important factor influencing operating profit on pasture based farms (Shalloo *et al.*, 2004) and that higher stocking rates (SR) are a key factor affecting productivity per hectare on pasture-based dairy farms for years (Macdonald *et al.,* 2008). Both McCarthy (2011) and Mac Donald (2008) have demonstrated that higher SRs result in a reduction in milk production per cow, but an increase in pasture utilisation and milk production per hectare. In comparison with other regions of Ireland, dairy production systems in the north-east are characterised by lower stocking rates (SR), a shorter grazing season and reduced farm profitability (Lapple *et al.,* 2012; Ramsbottom *et al.,* 2015). The objective of this study was to quantify the impacts of alternative SR and grazing season length combinations on animal and pasture productivity on a wetland soil in the northeastern region.

Materials and methods

This study was carried out at Ballyhaise Agricultural College (54° 015'N, 07° 031'W) during 2017. The experimental site is comprised of a variety of different soil types including alluvial, brown earth, gley and brown podzolic soils while the topography ranges from

alluvial flatlands to drumlins with steep slopes and U-shaped valleys. In January 2017, 120 spring calving dairy cows were randomly assigned pre-calving based on breed, parity, expected calving date and previous lactation milk yield (where available) to one of four grazing systems comprised of two grazing season (GS) lengths: average (AGS; 205 days; 15 March to 20 October) and extended (EGS; 270 days, 15 February to 20 November) and two SR treatments: medium (MSR; 2.5 cows/ha) and high (HSR; 2.9 cows/ha). Each experimental group had its own farmlet. While indoors, both AGS groups were fed a grass silage and concentrate diet. Weekly milk production was derived from individual milk yields recorded at each milking. Milk fat, protein and lactose concentrations were determined once weekly from successive morning and evening milk samples while individual body weight (BW) and body condition score (BCS) was recorded on a bi-weekly basis. Pre-grazing sward height (PreGSH) and post-grazing sward height (PostGSH) were measured using a rising plate meter (Jenquip, Feilding, New Zealand). Herbage mass (> 3.5 cm) was measured by cutting two quadrat samples per paddock before grazing. Least squares means for GS and SR were estimated using linear mixed models.

Results and discussion

There was no significant interaction between GS and SR on animal performance and so the main effects of GS and SR are presented in Table 1. Grazing season length varied from 209 days for both AGS treatments to 262 and 259 days for the MSR EGS and HSR EGS treatments, respectively. Neither SR nor GS had a significant effect on individual animal performance in terms of milk yield, milk composition, average BW or average BCS. Higher SR resulted in similar individual cow performance and significantly increased milk and milk fat plus protein production per hectare. Milk fat plus protein production varied from 1,132 and 1,136 kg / ha for the low SR average and extended treatments, respectively to 1,311 and 1,360 kg / ha for the high SR average and extended grazing treatments, respectively. There was no significant effect of SR or GS on grass growth (t/DM/ha) or grazed grass utilisation. As both AGS treatments were indoors for an additional 60 days between February and November, significantly more concentrate and silage were required during lactation compared with the EGS treatments. Both average turnout treatments consumed between 2.3–2.5 t silage DM/ha/yr compared to 0.9 and 1.4 t DM/ha/year for the respective extended grazing treatments. In addition, the average grazing season length treatments required 20% more concentrate than the comparable SR groups.

In a meta-analysis review of the effects of SR on animal performance McCarthy *et al.* (2011) reported a significant linear decline in individual animal performance as SR increased whereas no reduction was evident in the current study albeit within a narrow range of SR treatments. Similar to previous studies (O'Donovan *et al.*, 2004; Kennedy *et al.*, 2005), there was also no significant difference in herbage utilisation between the different grazing treatments in this experiment. Unlike O'Donovan *et al.* (2004) who found that the effects of spring-grazing date interacted with stocking rate for a number of milk production variables, no such interactions were observed in the current study over the entire lactation. Ultimately, the results suggest that extending the grazing season by 60 days delivers similar milk production performance to current average grazing season length but requires 100 kg less concentrate and 450 kg DM less silage per cow per year. A full economic appraisal of the production systems will be undertaken at the end of the project incorporating both animal performance and feed cost effects in addition to any other differences arising.

Table 1. Effect of Stocking Rate (SR) and Grazing Season length (GS) on animal performance and feed requirements

Grazing season length	Average		Extended		s.e.d.	P value		
Stocking rate	Medium	High	Medium	High		SR	GS	SR*GS
Milk yield (kg/cow)	5,224	5,154	5,056	5,287	113.6	0.47	0.87	0.18
Milk yield (kg/ha)	13,074	14,935	12,636	15,311	300.2	0.001	0.91	0.16
Fat plus protein yield (kg/cow)	452	452	454	470	10.5	0.45	0.34	0.46
Fat plus protein yield (kg/ha)	1,132	1,311	1,136	1,360	28.3	0.001	0.34	0.41
Grazed grass utilisation (t DM/ha)	9.6	10.4	10.7	11.6	0.76	0.27	0.15	0.88
Concentrate fed (t DM/ha)	1.4	1.6	1.1	1.3	0.04	0.001	0.001	0.78
Silage fed (t DM/ha)	2.3	2.5	0.9	1.4	0.12	0.01	0.001	0.22

Conclusion

The results of this study show the potential of both extended grazing and higher SR to support increased milk productivity while reducing supplementary feed requirements. Increasing SR resulted in similar milk production per cow and significantly increased milk output per hectare.

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References

Dillon, P.J.R. Roche, L. Shalloo and B. Horan. (2005). Optimising financial return from grazing in temperate pastures. Pages 131-147 in Utilization of Grazed Grass in Temporal Animal Systems. J.J. Murphy, ed. Wageningen Acad. Publ., Wageningen, The Netherlands.

Finneran, E., P. Crosson, M. Wallace, P. O'Kiely, D. Forristal and L. Shalloo. (2010). Simulation modelling of the cost of producing and utilising feeds for ruminants on Irish farms. *J. Farm Manage*, 14: 95–116.

Holmes, C.W., Hoogendoorn, C.J., Ryan, M.P. and A.C.P.Chu. (1992). Some effects of herbage composition, as influenced by previous grazing management, on milk production by cows grazing on ryegrass/white clover pastures. 1. Milk production in early spring: effects of different regrowth intervals during the preceding winter period. *Grass and Forage Science,* 47: 309–315.

Kennedy, E., O'Donovan, M., Murphy, J.P., Delaby, L. and F.P. O'Mara. (2005). Effects of grass pasture and concentrate based feeding systems for spring calving dairy cows in early spring on lactation performance. *Grass and Forage Science,* 60: 310–318.

Läpple, D., T. Hennessy and M. O'Donovan. (2012). Extended grazing: A detailed analysis of Irish dairy farms. *Journal of Dairy Science,* 95: 188–195.

Macdonald, K.A., J.W. Penno, J.A. S Lancaster and J.R. Roche. (2008). Effect of stocking rate on pasture production, milk production and reproduction of dairy cows in pasture-based systems. *Journal of Dairy Science,* 91: 2151–2163.

McCarthy, B., L. Delaby, K.M. Pierce, F. Journot and B. Horan. (2011). Meta-analysis of the impact of stocking rate on the productivity of pasture-based milk production systems. *Animal,* 5: 784–794.

O'Donovan, M., Delaby, L. and J.L. Peyraud. (2004). Effect of time of initial grazing date and subsequent stocking rate on pasture production and dairy cow performance. *Animal Research,* 53: 489–502.

Ramsbottom, G., B. Horan, D.P. Berry and J.R. Roche. (2015). Factors associated with the financial performance of spring-calving, pasture-based dairy farms. *Journal of Dairy Science*, 98: 3526–3540.

Shalloo, L., P. Dillon, J. O'Loughlin, M. Rath and M. Wallace. (2004). Comparison of a pasture-based system of milk production on a high rainfall, heavy-clay soil with that on a lower rainfall, free-draining soil. *Grass and Forage Sci.,* 59**:** 157–168.

The effect of alternative autumn feed budgeting and grazing strategies on animal performance and pasture productivity within intensive grass-based spring milk production systems

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Abstract

Increasing stocking rates on Irish dairy farms may result in increased feed supplementation and a shortening of the grazing season unless grazing management practices are adapted to increase pasture supply during late autumn and early spring. The objective of this study was to evaluate the impact of three autumn pasture supply strategies and two farm system intensities on the performance of spring calving dairy cows during late lactation. The experiment was a randomised block design with a 3 × 2 factorial arrangement of treatments. In each year, the six experimental treatments consisted of three whole-farm pasture supply (**PS**) strategies (Low Pasture Supply (**LPS**; 400 kg DM/ha available at winter housing), Standard Pasture Supply (**MPS**; 600 kg DM/ha available at winter housing) and High Pasture Supply (**HPS**; 800 kg DM/ha available at winter housing)) and two whole farm system (FS) intensities (Medium Intensity (**MI**; 2.75 cows/ha plus 90% pasture diet) and High Intensity (**HI**; 3.25 cows/ha and 80% pasture diet)). There was no difference in DHA between the three PS treatments during autumn (15.1 kg DM/cow/d) while mean post-grazing height, post-grazing biomass yield and herbage removal increased with increasing PS. Despite the significant effect of PS treatment on pre-grazing herbage yield, the extended residency time of MPS and HPS treatments resulted in increased herbage utilisation per ha and similar herbage utilisation per cow for all treatments. Despite large differences in pre-grazing herbage yield in the current study, PS had no significant effect on animal performance during autumn. Feed system had no significant effect on pre-grazing measurements, with the exception of DHA which was higher ($P < 0.01$) for MI (15.8 kg DM/cow/d) compared with HI (14.3 kg DM/cow/d). The combination of increased SR and increased concentrate supplementation within HI FS resulted in reduced post-grazing biomass yields, increased herbage utilisation and increased fat plus protein production per cow compared to MI. These results highlight the potential for high intensity grazing systems to maintain an extended grazing season by increasing PS during autumn without detriment to individual animal performance.

Keywords: dairy cow, stocking rate, pasture supply, milk production

Introduction

The overall resilience and long term sustainability of the pasture-based dairy industries is dependent on increased productivity and improved efficiency of conversion of grazed pasture to animal products (Delaby and Horan, 2018). The potential of Irish pasture-based dairy farms to expand output can be realised through a variety of changes: increase cow numbers and area farmed, intensification of production by increasing cow numbers on existing area or increasing productivity per existing cow by increasing both the use of and efficiency of available feeds. Stocking rate (**SR**), defined as the number of animals per unit area of land used during a specified defined period of time (cows/hectare), is widely acknowledged as the main driver of productivity within grazing systems (McCarthy *et al.*, 2013). Although the current average mean SR is 1.9 LU per hectare on Irish dairy farms,

many dairy farmers are now increasing overall farm SRs to increase milk output post milk quotas. Increasing SR places added feed demands on the available land area and can result in increased feed supplementation and a shortening of the grazing season length unless grazing management practices are adapted (Roche *et al.,* 2017).

Striking the correct balance between herbage quality and quantity is a key driver in pasture-based production systems with pasture supply and pre-grazing herbage yield two critical factors that influence animal performance. As grazing systems intensify, grazing management strategies including feed budgeting, rotation planning and grazing intensity must also be adjusted to optimise the productivity of intensive systems and support the increased feed demands of grazing dairy herds (Delaby and Horan, 2018). Altering autumn grazing management to increase pasture supply can allow higher SR farms to maintain an extended grazing season while continuing to harness the benefits of a predominantly pasture-based diet. At the same time, increasing pasture supply via extended rotations during autumn may also result in increased sward stem and dead material components (Tunon *et al.*, 2015) resulting in reduced sward quality (Beecher *et al.,* 2018) and reduced animal intake and performance (Lawrence *et al.*, 2017). In this context, the potential for altered autumn grazing management practices both in terms of grass supply, rotation lengths and grazing intensities to support high pasture utilisation requires further investigation. The hypothesis of this study is that increased pasture supply can be an effective strategy to maintain animal performance on a predominantly grazing diet during autumn.

Materials and methods

The experiment was undertaken at the Animal and Grassland Research and Innovation Center, Teagasc Moorepark, Ireland (50°7N; 8°16W) in autumn 2017. A total of 140 cows were used. It formed part of a larger study designed to examine the biological and economic impact of alternative SR and pasture management combinations on animal and pasture performance.

The experiment was a randomised block design with a 3 × 2 factorial arrangement of treatments. In each year, the six experimental treatments consisted of three whole-farm pasture supply strategies and two whole farm systems (Medium intensity (MI, 2.75 cows/ha) and High intensity (HI, 3.25 cows/ha). Cows within each breed were randomly assigned pre-calving based on expected calving date, parity, and EBI to one of three pasture supply treatments: Low Pasture Supply (LPS; 650 kg DM/ha available at calving start date), Standard Pasture Supply (MPS; 900 kg DM/ha available at calving start date) and High Pasture Supply (HPS; 1,150 kg DM/ha available at calving start date). The LPS treatment group was designed to reflect prevailing pasture management practice on Irish commercial dairy herds based on national data statistics (Pasturebase Ireland; Hanrahan *et al.,* (2017)) while the MPS and HPS treatments represented two incremental increases in pasture supply which may be appropriate within intensive dairy production systems. In order to achieve the desired differences in pasture availability during autumn, rotation length was extended by two days per week from 31 July, 15 August and 31 August for the LPS, MPS and HPS, respectively. The differences in pasture supply created were maintained through autumn. The FS treatments were designed to reflect medium and high intensity grazing systems which are typical on Irish commercial dairy farms during autumn. The MI FS corresponded to a moderate overall SR system (2.75 cows/ha) with no supplementary feed and a post grazing residual of 4 cm while the HI FS had a higher SR (3.25 cows/ha) and was supplemented with 1.8 kg concentrate DM per cow per day, and had a target post grazing residual of 3.5 cm. The experimental animals used in this study comprised both high Economic Index (EBI) Holstein-Friesian (HF) and Holstein-Friesian Jersey crossbreds (JFX) with an average EBI, milk, fertility, calving, beef, maintenance, management, and health sub-indices of €173, €59, €63, €41, €-23, €26, €4 and €3 respectively.

A total of 48.1 ha of permanent grassland predominantly perennial ryegrass (*Lolium perenne*) was used for the duration of the experiment. Each of the six treatments had a separate farmlet of 18 paddocks, with each farmlet balanced for location block, sward species and soil type. Each farmlet received an annual chemical nitrogen (N) fertiliser application of 250 kg N/ha per year. Grazing management was accomplished by weekly monitoring of farm pasture supply within each treatment. The MI and HI farm systems were grazed in sub-paddocks adjacent to each other (with similar target pre-grazing herbage mass, and residency time). Grazing data were collected from all paddocks grazed during each grazing rotation in autumn 2017 (1 August to 20 November) using the methods outlined previously by Delaby and Peyraud (1998). Weekly milk production was derived from individual cow milk yield (kg) recorded at each milking (Dairymaster, Causeway, Co. Kerry, Ireland). Milk fat, protein and lactose concentration for each cow was determined from successive pm and am milkings using a Milkoscan 203 (Foss Electric DK-3400, Hillerod, Denmark) and subsequently, fat, protein, lactose, and MS yields were calculated.

Statistical Analysis

The effect of pasture supply (PS), farm system (FS), paddock and month on net herbage accumulation, chemical composition of herbage, pre-grazing HM, pre and post-grazing compressed sward height, daily herbage allowance, daily herbage removal, herbage utilisation and concentrate and forage supplementation were analysed using mixed models (PROC MIXED; (SAS_Institute, 2010). Paddock was included as random effect in the model. The effect of PS, FS, parity, breed, calving date, lactation week, genetic merit, and their interactions on milk, fat, protein, lactose and MS yield per cow were analysed using mixed models (PROC MIXED; SAS Institute, 2010). Milk, fat, protein, lactose and fat plus protein (milk solids; MS) yield were analysed with the effect of PS, FS, block and their interactions included in the model.

Results and discussion

Pasture Accumulation, Grazing Characteristics and Dietary Details

Daily grass growth significantly decreased during autumn ($P < 0.001$) from 58 kg DM/ha/d in September to 42 and 33 kg DM/ha/d in October and November, respectively. There was no significant interaction of PS with FS on autumn sward measurements and so only the main effects are presented in Table 1. Before grazing, mean paddock pre-grazing height, pre-grazing herbage yield and sward density were significantly higher with increased PS ($P < 0.001$). Mean paddock residency time significantly increased with increased PS ($P < 0.001$) averaging 2.3, 2.5 and 3.1 days for LPS, MPS and HPS, respectively. There was no difference in DHA between the three PS treatments (15.1 kg DM/cow/d). After grazing, mean post-grazing height, post-grazing biomass yield and herbage removal increased with increasing PS ($P < 0.001$). Grazing efficiency was higher for LPS compared to both MPS and HPS ($P < 0.001$). Similar to DHA, there was no difference in herbage utilisation per cow between the PS treatments although the higher PS treatments achieved increased herbage utilisation per hectare. There was also no significant effect of FS on pre-grazing measurements, with the exception of DHA which was higher ($P < 0.01$) for MI (15.8 kg DM/cow/d) compared with HI (14.3 kg DM/cow/d). As per the experimental design, there was a significant effect of FS on post-grazing height ($P < 0.01$), post-grazing biomass ($P < 0.05$), grazing efficiency ($P < 0.05$) and herbage utilisation per hectare ($P < 0.05$).

Table 1. The effect of Pasture Supply (PS) and Farm System (FS) on pasture characteristics during autumn

	Pasture Supply[1]			Farm System[2]		s.e.	Significance[3]	
	LPS	MPS	HPS	MI	HI		PS	FS
Pre-grazing swards								
Sward height (cm)	10.1[a]	10.3[a]	12.0[b]	10.8	10.8	0.30	***	NS
Herbage yield (kg DM/ha)	1,616[a]	1,793[a]	2,338[b]	1,862	1,970	100.0	***	NS
Sward density (kg DM/cm)	237[a]	254[ab]	271[b]	250	258	5.1	**	NS
Average residency (days)	2.3[a]	2.5[b]	3.1[c]	2.6	2.6	0.05	***	NS
Herbage allowance (kg DM/ cow/d)	14.3	15.1	15.8	15.8	14.3	0.38	NS	**
Post-grazing swards								
Sward height (cm)	3.5[a]	3.7[a]	3.9[b]	3.8	3.6	0.09	***	**
Herbage yield (kg DM/ha)	5[a]	49[a]	123[b]	85	33	14.7	***	*
Grazing efficiency (%)	102[a]	98[b]	96[b]	97	100	0.9	***	*
Herbage removal (kg DM/ha)	1,613[a]	1,743[a]	2,216[b]	1,776	1,938	58.6	***	*
(kg DM/cow/d)	14.4	14.3	14.3	14.6	14.0	0.41	NS	NS

[1]Pasture supply (PS): Low (LPS), Medium (MPS), High (HPS); [2]Farm system (FS): Medium Intensity (MI), High Intensity (HI); [3]Significance:†$P \leq 0.10$; *$P < 0.05$; **$P < 0.01$; ***$P < 0.001$

There was no significant PS by FS interaction on milk production and composition variables and so only the main effects are presented (Table 2). Pasture supply had no significant effect on milk production variables although milk protein content tended to increase with increased pasture supply. There was also no significant effect of FS on daily milk yield, fat, protein and lactose composition during autumn. Feed system had a significant ($P < 0.05$) effect on daily MS yield due to the superior performance of the HI FS treatment.

Table 2. The effect of Pasture Supply (PS) and Farm System (FS) on animal performance during autumn

	Pasture Supply[1]			Farm System[2]		s.e.	Significance[3]	
	LPS	MPS	HPS	MI	HI		PS	FS
Milk yield (kg/cow/d)	15.6	15.1	15.2	15.1	15.5	0.42	N.S.	N.S.
Fat content (g/kg)	55.9	57.5	56.0	56.3	56.6	0.80	N.S.	N.S.
Protein content (g/kg)	40.0	41.0	40.6	40.6	40.5	0.28	†	N.S.
Lactose content (g/kg)	46.9	46.6	46.8	46.8	46.7	0.18	N.S.	N.S.
Fat plus protein yield (kg/ cow/d)	1.46	1.45	1.43	1.42	1.47	0.035	N.S.	*

[1]Pasture supply (PS): Low (LPS), Medium (MPS), High (HPS); [2]Farm system (FS): Medium Intensity (MI), High Intensity (HI); [3]Significance:†$P \leq 0.10$; *$P < 0.05$; **$P < 0.01$; ***$P < 0.001$

The extended experimental time period (15 wk from 1 August to 20 November) provided an ideal opportunity to assess the cumulative autumnal effects on milk and pasture production. Despite the significant effect of PS treatment on pre-grazing herbage yield, the extended residency time of MPS and HPS treatments resulted in increased herbage utilisation per ha and similar herbage utilisation per cow for all treatments. Although previous studies have associated increasing PS with a decline in animal performance in high PS swards (Hennessy *et al.*, 2006; Lawrence *et al.,* 2017), the large differences in pre-grazing herbage yield in the current study (600 kg of DM/ha difference between treatments) had no significant effect on animal performance similar to McEvoy *et al.* (2009). The combination of increased SR and increased concentrate supplementation within the HI FS resulted in reduced post-grazing biomass, increased herbage utilisation and increased fat plus protein production compared to MI. These results highlight the potential for intensive grazing systems to maintain an extended grazing season with MI and HI FS by increasing PS during autumn without detriment to individual animal performance.

Conclusion

Increasing pasture supply via extended autumn rotation lengths resulted in increased pre-grazing herbage yields, increased paddock residency times and increased pasture removal during autumn. The increased pre-grazing herbage yield arising from higher PS had no effect on the late lactation milk production performance of spring calving dairy cows. Equally, the results indicate that the combination of reduced post-grazing sward heights and increased concentrate supplementation of higher SR grazing systems can increase both grazing efficiency and individual animal performance during autumn.

References

Delaby, L. and Horan, B. (2017). Improved efficiency in temperate grass based dairy systems. In *Proceedings of the 54ª Reunião Anual da Sociedade Brasileira de Zootecnia*, 24 a 28 de Julho de 2017 – Foz do Iguaçu – Brasil. ISSN 1983-4357, 133–145.

Delaby, L. and Peyraud, J.L. (1998). Effect of a simultaneous reduction in nitrogen fertilization and stocking rate on the performance of dairy cows and pasture utilization. *Annales de Zootechnie,* 47: 17–39.

Hanrahan, L., Geoghan, A., O'Donovan, M., Griffith, V., Ruelle, E., Wallace, M. & Shalloo, L. (2017). PastureBase Ireland: A grassland decision support system and national database. *Computers and Electronics in Agriculture,* 136: 193–201.

Hennessy, D., O'Donovan, M., French, P. & Laidlaw, A. (2006). Effects of date of autumn closing and timing of winter grazing on herbage production in winter and spring. *Grass and Forage Science,* 61**:** 363–374.

Hoden, A., Peyraud, J., Muller, A., Delaby, L., Faverdin, P., Peccatte, J. & Fargetton, M. (1991). Simplified rotational grazing management of dairy cows: effects of rates of stocking and concentrate. *The Journal of Agricultural Science,* 116**:** 417–428.

Horan, B. and Roche, J.R. (2018). Defining resilience in pasture-based dairy farm systems in temperate regions. *Animal Production Science* In press.

Lawrence, D., O'Donovan, M., Boland, T. & Kennedy, E. (2017). Effects of autumn and spring defoliation management on the dry-matter yield and herbage quality of perennial ryegrass swards throughout the year. *Grass and Forage Science,* 72**:** 38–49.

Macdonald, K., Penno, J., Lancaster, J. & Roche, J. (2008). Effect of stocking rate on pasture production, milk production, and reproduction of dairy cows in pasture-based systems. *Journal of dairy Science,* 91**:** 2151–2163.

McCarthy B., Delaby, L., Pierce, K., Brennan, A. & Horan, B. (2013). The effect of stocking rate and calving date on milk production of Holstein–Friesian dairy cows. *Livestock Science,* 153**:** 123–134.

McEvoy M., O'Donovan, M., Kennedy, E., Murphy, J.P., Delaby, L. & Boland, T.M. (2009). Effect of pregrazing herbage mass and pasture allowance on the lactation performance of Holstein-Friesian dairy cows. *Journal of Dairy Science,* 92: 414–422.

Roche J.R., Berry, D.P., Bryant, A.M., Burke, C.R., Butler, S.T., Dillon, P.G., Donaghy, D.J., Horan, B., Macdonald, K.A. & macmillan K.L. (2017). A 100-Year Review: A century of change in temperate grazing dairy systems. *Journal of Dairy Science,* 100: 10189–10233.

SAS Institute 2010. User's Guide: Statistics. Version 9.3. SAS Institute Inc., Cary, NC.

Tuñon G, Kennedy, E., Horan, B., Hennessy, D., Lopez-Villalobos, D., Kemp, P., Brennan, A. & O'Donovan, M. (2014). Effect of Grazing Severity on Perennial Ryegrass Herbage Production and Sward Structural Characteristics Throughout an Entire Grazing Season. *Grass and Forage Science,* 69: no. 1: 104–118.

Determination of enteric methane emissions of dairy cows fed with different diets and relationship with milk yield and ruminal function in order to improve advice for farmers

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Abstract

Methane from ruminal fermentation, termed enteric methane, contributes 40% of the total agricultural emissions. Mitigation of methane production could allow for a reduction in the impact of livestock on climate change and may improve the public perception towards this sector. Milk yield, methane emissions, carbon footprint and dietary costs were measured in experimental and commercial farms in different diet conditions: enriched fat diet (linseed or canola), high concentrate diet, high level of starch in diet or grazing. Individual milk samples were analysed monthly for milk quality and for methane emissions predicted by milk spectra analysis. The first results showed that methane emissions per kg of milk can vary from 11–20 g. Preliminary comparison between the diets demonstrated that feeding with grazed grass was beneficial in terms of feeding costs and environmental impact while methane emissions per kg milk were higher. Diets with low fibre content can have a beneficial impact to decrease methane emissions but could disturb ruminal function. These results will allow us to predict methane emissions and environmental impacts of milk production according to the diet composition, dietary costs, lactation stage and milk production. From these results, advice about feeding strategies could be given to reach the best compromise between environmental and economic objectives.

Keywords: animal nutrition, methane emissions, ruminal function, dairy sector, greenhouse gases

Introduction

Methane emissions from enteric fermentation of livestock are responsible for 40% of greenhouse gas (GHG) emissions from the agricultural sector (Gerber *et al.*, 2014). According to the literature, several strategies are available to mitigate these emissions (Knapp *et al.*, 2014; Martin *et al.*, 2010). One of them is the nutritional approach that aims to change ruminal fermentation patterns to decrease methane production. In this context, the first objective of the Life Dairyclim project was to optimise the feeding strategies during the winter (barn feeding) and the summer (grazing and supplementary feeding) and to evaluate the impact of these different diets on methane emissions and carbon footprint of milk. The tested feeding strategies were selected to be close to the usual rations given to dairy cows in Wallonia, Belgium. The zootechnical and economic aspects were also investigated.

Material and methods

The trials were conducted during the Life Dairyclim project that began in October 2015. The experimental design was the same for all the trials i.e. experimental groups receiving concentrate of different composition confronted with groups receiving control concentrate. During the first period of the project, 2015-2016, two different concentrate compositions were tested at the experimental farm of Sart Tilman (ULg) in Liège (Belgium); one being rich in starch (ST), the other one being rich in fat (FAT). In 2016–2017, trials were focused on concentrates rich in fat, composed of extruded linseed (Concentrate 1- ELS)

and of extruded canola seed (Concentrate 2- CS). These trials were held at the Centre of Agronomic Technologies (CTA Belgium). The groups were balanced on the basis of days in milk (DIM) and lactation number (LN). During all the trials the cows received a diet composed of silages and by-products (total mixed ration = TMR), similar to the diets that Walloon farmers usually offer to their dairy herd (Table 1). Concentrates were provided at the feeding bin of the robot (ULg) or at the automatic concentrate feeder (CTA) as a complement to the TMR. The rations were calculated to ensure the same inputs in Control and Test groups and the amount of concentrates to be delivered was calculated on the basis of milk yield and days in milk (DIM). The ration differed by the amount of starch or fat. Nutritional composition of the diets offered during the different trials are presented on Table 2.

Table 1. Rations offered to the cows in 2015 and 2016

	2015-2016		2016-2017	
% DMI	**Ration offered (ST vs control)**	**Ration offered (Fat vs control)**	**Ration offered (ELS vs control)**	**Ration offered (CS vs control)**
Grass silage	29	28	22	27
Maize silage	24	22	26	29
Ensiled beet pulp	9	8	11	14
Brewers	5	5	-	-
Cereal crop silage	-		11	-
Hay	5	4	-	-
Straw	2	2	-	-
Concentrate rich in protein	9	9	9	7
Tested concentrate	17	22	21	21
Total DMI	19.5 kg	20.6 kg	24.6 kg	24.1 kg

Abbreviations: DMI: dry matter intake; ST: starch group; ELS:extruded linseed; CS: canola seed

Table 2. Nutritional composition of the different rations

g/kgDM	**TMR + control**	**TMR + ST**	**TMR + control**	**TMR + Fat**	**TMR + control**	**TMR + ELS**	**TMR + control**	**TMR + CS**
DM	430	430	437	437	360	360	360	360
CP	149	145	157	155	158	158	149	148
Starch	108	132	112	124	139	151	142	157
Fat	37	37	37	43	36	48	34	47
NDF	352	395	324	386	410	391	413	392

Abbreviations: DM: dry matter; TMR: total mixed ration; ST: starch; ELS: extruded linseed; CS: canola seed; CP: crude protein

Trials were performed also on grazing cows. In 2017, two contrasting rations were tested regarding enteric methane emissions and carbon footprint of produced milk during 72 d.

Therefore, cows receiving a dry ration (DR group) were compared with those whose ration was composed of grazed grass (G group). The DR group ration was composed of 12.2 kg DM concentrates, 1.7 kg DM straw, 0.7 kg DM molasses and 3.6 kg DM alfalfa pellets while the G group grazed day and night. Concentrates (3.5 kg, 16% CP) were allocated in both groups to allow passage to the automatic concentrate feeder. In 2018, a gradient of grazed grass was tested within three groups: one receiving 100% grazed grass (group 100%), the second 50% (group 50%) and the third one 0% (group 0%) during 45 d. Concentrates (16% CP) were supplied at the automatic concentrate feeder (2 $kg.cow^{-1}d^{-1}$). The TMR of Group 0 and 50% were based on forages (88%). The DMI (dry matter intake) of each group was targeted at 20 kg DM with an energy input of 20 kVEM. Methane emissions were calculated by two methods: the measurements of the CH_4 emitted in breath samples using the Guardian® inserted in the feeding bin of the robot (Sart Tilman) or in the automatic concentrate feeder (CTA) and by predictions based on analysis of the milk spectra (Vanlierde *et al.*, 2016). The results obtained with the Guardian® are not presented in this publication.

Milk yield and concentrate consumption were recorded on a daily basis.

Carbon footprint of diets was calculated using the LCA methodology with Feedprint® model tool (Vellinga *et al.*, 2014).

Feeding costs were calculated on the basis of purchase invoices. The silage production costs were estimated by the software "Dégâts du gibier" developed by Fourrages Mieux ASBL. Costs of grazed grass took into consideration the grass yield and inputs to the pastures.

At grazing, grass availability was assessed on the basis of grass height measurements.

Statistical analysis

Data were at first analysed by descriptive statistic methods (proc means and proc univariate –SAS 9.3). Proc mixed modelling was used to take into account repeated measurements (repeated days/subject animal) and a covariance analysis type AR(1) in 2015–2016 and type cs in 2016–2017. The models that most adapted to the trials were chosen on the basis of AIC criteria. These procedures were repeated for each trial period: Trial with concentrate rich in starch and concentrate rich in fat in 2015–2016 and in 2016–2017 for the trial ELS, trial CS and grass experiments in 2017 and 2018.

Results

The results of the different trials are presented in Table 3, 4, 5 and 6. In 2015–2016, no statistical difference was observed. In 2016–2017, methane emissions ($g.cow^{-1}.d^{-1}$) were decreased in ELS and CS compared with control groups. The decrease in methane g.kg $milk^{-1}$ reached more than 10% in ELS group. During the summer trials, different results were observed. The comparison between the dry ration and the 100% grazing demonstrated lower methane emissions with the DR whatever the chosen unit. In trials held in 2018, lower daily methane emissions per cow were observed in the group 0%. The methane production per kg milk and per kg ECM showed no difference between the groups.

Table 3. Results of Trial Starch (ST) and Fat (FAT) conducted in 2015–2016

	Control	ST	Sig	Control	FAT	Sig
MY (kg $cow^{-1}.d^{-1}$)	28.3 ± 1.5	24.8 ± 1.6	***	29.3 ± 1.2	30.4 ± 1.2	ns
% Fat	3.6 ± 0.1	3.7 ± 0.1	ns	3.8 ± 0.1	3.7 ± 0.1	ns
% Protein	3.4 ± 0.1	3.4 ± 0.1	ns	3.3 ± 0.0	3.3 ± 0.0	ns
ECM (kg $cow^{-1}.d^{-1}$)	26.9 ± 1.4	23.7 ± 1.4	***	28.6 ± 1.2	29.4 ± 1.2	ns
CH4 (g $cow^{-1}.d^{-1}$)	416 ± 10	424 ± 10	ns	465 ± 7	459 ± 7	ns
CH4 (g kg^{-1}milk)	16.1 ± 1.1	19.3 ± 1.1	**	17.0 ± 0.8	16.4 ± 0.8	ns
CH4 (g kg^{-1}ECM)	16.7 ± 1.0	19.9 ± 1.0	*	17.4 ± 0.8	16.9 ± 0.8	ns
Concentrate intake (kgDM $cow^{-1}.d^{-1}$)	3.4 ± 1.7	3.4 ± 1.7	ns	5.3 ± 1.7	5.1 ± 1.7	ns

Abbreviations: MY: milk yield; ECM: energy corrected milk. Values are LSmeans ± SE. The statistics results show the group effect. ns: not significant; *: $p < 0.05$; **: < 0.01; ***: $p < 0.001$

Table 4. Results of Trial with extruded linseed (ELS) and canola seed (CS) conducted in 2016-2017

	Control	ELS	Sig	Control	CS	Sig
MY (kg $cow^{-1}.d^{-1}$)	34.4 ± 0.5	36.6 ± 0.5	***	34.8 ± 0.7	36.3 ± 0.7	trend
% Fat	4.0 ± 0.1	3.8 ± 0.1	*	3.8 ± 0.1	3.8 ± 0.1	ns
% Protein	3.7 ± 0.0	3.2 ± 0.0	***	3.4 ± 0.1	3.3 ± 0.1	ns
ECM (kg $cow^{-1}.d^{-1}$)	34.4 ± 0.5	35.3 ± 0.5	ns	34.7 ± 0.8	34.9 ± 0.8	ns
CH4 (kg $cow^{-1}.d^{-1}$)	485 ± 4	462 ± 4	***	475 ± 7	469 ± 7	ns
CH4 milk (g kg^{-1}milk)	14.6 ± 0.2	12.9 ± 0.2	***	14.1 ± 0.4	13.1 ± 0.4	*
CH4 ECM (g kg^{-1}ECM)	14.4 ± 0.2	13.4 ± 0.2	***	14.3 ± 0.4	13.9 ± 0.4	ns
Concentrate intake (kgDM $cow^{-1}.d^{-1}$)	5.0 ± 0.2	4.6 ± 0.2	***	4.8 ± 0.2	4.8 ± 0.2	ns

Values are LSmeans ± SE. Abbreviations: MY: milk yield; ECM: energy corrected milk. The statistics results indicate the group effect. ns: not significant; trend: 0.1; *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$

Table 5. Results of Trial DR. Group DR: received a dry ration and Group G was 100% grazing

	Dry Ration	Grazing	Sig
MY (kg.$cow^{-1}.d^{-1}$)	36.3 ± 1.4	26.1 ± 1.4	***
% Fat	3.0 ± 0.1	3.5 ± 0.1	***
% Protein	3.1 ± 0.0	3.0 ± 0.0	ns
ECM (kg.$cow^{-1}.d^{-1}$)	31.3 ± 1.2	23.9± 1.2	***
CH4 (kg.$cow^{-1}.d^{-1}$)	435 ± 10	451 ± 10	ns
CH4 (g.kg^{-1}milk)	12.3 ± 0.5	18.1 ± 0.5	***
CH4 ECM (g.kg^{-1}ECM)	14.2 ± 1.0	19.8 ± 1.0	***

Values are LSmeans ± SE. Statistical values indicate the group effect.. ns: not significant; trend: 0.1; *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$

Table 6. Results of the Trial 0%. 50%. 100% grass

	0% grass	50% grass	100% grass	Sig
MY (kg cow^{-1} d^{-1})	28.5 ± 1.3	27.2 ± 1.2	25.2 ± 1.3	ns
ECM (kg cow^{-1} d^{-1})	27.5 ± 1.5	25.2 ± 1.4	24.2 ± 1.5	ns
% Fat	3.7 ± 0.2	3.8 ± 0.2	3.6 ± 0.2	ns
% Protein	3.2 ± 0.1	3.2 ± 0.1	3.1 ±0.1	ns
CH4 (kg cow^{-1} d^{-1})	475 ± 9^{a}	440 ± 9^{b}	430 ± 9^{b}	*
CH4 (g kg^{-1}milk)	17.7 ± 1.1	17.3 ± 1.1	17.9 ± 1.1	ns
CH4 ECM (g.kg^{-1}ECM)	18.3 ± 0.9	17.9 ± 0.9	19.3 ± 0.9	ns

Values are LSmeans ± SE; ns: not significant; *: $p < 0.05$.

Feeding costs

The impact of the different diets on feeding costs was evaluated. Independently from the study's year, full grazing diets were the cheapest per cow per day or per 100 kg milk produced (Table 7).

Table 7. Feeding costs of all the studied diets. Costs are expressed in € per cow and per day or per 100 kg milk produced

		Feeding costs		
		Per cow.d €	Per 100 kg milk €	Milk yield (kg cow^{-1}.d^{-1})
2015-2016	Control feed	3.98	14.0	28.3
	ST	4.03	16.2	24.8
	FAT	4.35	14.3	30.4
2016-2017	Control feed	4.22	11.8	34.6
	ELS	4.35	12.2	36.8
	Control feed	4.12	12.1	33.9
	CS	4.31	11.9	36.0
	DR	5.93	16.5	36.3
	G	1.98	8.0	26.1
2018	0%	4.73	16.6	28.5
	50%	3.36	12.3	27.2
	100%	2.19	8.7	25.2

Climate impact of tested diet

The climate impact of each diet was evaluated by checking the carbon footprint total of each feedstuff. Values of silages and grazed grass were adapted in relationship with their DM. Values were put in correlation with the evaluated control diet. Values are expressed per kg milk and kg ECM.

Climate impact (g eqCO_2) per kg milk and per kg ECM was estimated for all the tested diets.

The CF of tested compounds were generally higher than control ones. The diet incorporating grazed grass had generally a lower CF than the control ones (Table 8).

Table 8. Climate impact (g eqCO_2) per kg milk and per kg ECM for all the tested diet

Year of trial	Tested diet	g eq CO_2/kg milk	g eq CO_2/kg ECM
2015-2016	Control	269	283
	ST	308	323
	Control	234	274
	Fat	256	274
2016-2017	Control	308	312
	ELS	315	318
	Control	297	307
	CS	311	323
	DR	498	576
	G	356	390
2018	0%	363	377
	50%	339	362
	100%	322	353

Discussion

Diminution in enteric methane emissions were noted when compounds rich in fat (Fat; ELS; CS) were added to the total mixed ration. It must be highlighted that a substantial amount has to be given to reach a noticeable effect. The use of these components is to be limited to early calving cows. The higher the milk yield, the higher enteric methane reduction. At grazing, no effect on methane emissions per cow per day was observed possibly because of high grass quality. Conversely, the decrease in milk yield observed for full grazing diets induced an increase in methane emissions per kg produced in 2017. This observation was not confirmed in 2018. The carbon footprint in relation to the provided diet took into consideration only the climate impact and not other environmental indicators, like biodiversity index or land use change. Values are dependent on forage quality. For example, the dry matter of silages has a huge impact on figures. Use of each tested concentrate increased the carbon footprint of the diet while grazing decreased it. However, the impact was moderate. The incorporation of concentrate rich in fat induced an increase in production costs that was partly attenuated by the higher milk production. Grazing was the most beneficial in terms of feeding costs.

Conclusion

This compilation of trials' results over several years highlights the difficulty to get a unique overview of the effects of introducing new compounds in cows' diets. Some negative effects could counteract the positive effects observed when a change is made. Advisors should keep in mind this difficulty.

Acknowledgements

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References

Gerber, P.J., Steinfeld, H., Henderson, B., Mottet, A., Opio, C., Dijkman, J., Falucci, A., Tempio, G. (2014). Lutter contre le réchauffement climatique grâce à l'élevage. Une évaluation des émissions et des opportunités d'attenuation au niveau mondial. Organisation des nations Unies pour l'alimentation et l'agriculture.

Knapp, J.R., Laur, G.L., Vadas, P.A., Weiss, W.P., Tricarico, J.M. (2014). Invited review: Enteric methane in dairy cattle production: Quantifying the opportunities and impact of reducing emissions. *Journal of Dairy Science*, 97: 3231–3261.

Martin, C., Morgavi, D., Doreau, M. (2010). Methane mitigation in ruminants: From microbe to the farm scale. *Animal*, 4(3): 351–365.

Vanlierde, A., Vanrobays, M.L., Gengler. N., Dardenne, P., Froidmont, E., Soyeurt, H., Dehareng. F. (2016). Milk mid-infrared spectra enable prediction of lactation-stage-dependent methane emissions of dairy cattle within routine population-scale milk recording schemes. *Animal Production Science*. 56(3). 258–264. https://doi.org/10.1071/AN15590.

Vellinga TH.V. Blonk H. Marinussen M. Zeist W.J van. Starman D.A.J. Methodology used in FeedPrint: a tool quantifying greenhouse gas emissions of feed production and utilization (2014) Wageningen UR Livestock Research SN - 1570–8616.UR - http://edepot.wur.nl/254098.

The need for new bio-economic modelling approaches in precision livestock farming

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Abstract

Livestock farming represents a complex biological system where farmer has to continuously make decisions under many constraints (animal welfare, antimicrobial use, price volatility.…). This work proposes an integrated bioeconomic modelling to highlight the need for holistic approaches for PFL technology evaluation. We developed a biological model of dairy herd dynamics that simulated herd population, cow reproduction, milk production and health on the basis of cow-week events. The cow-week occurrence of diseases was based on basic incidences, cow specific risk factors and herd contamination risks. The health disorders affect milk production, mortality risk, food needs and reproduction performances. This biological model was combined with an economic optimisation model which dynamically represents farmer's input allocation decisions while maximising his utility under constraints (welfare, antimicrobial use, cash flow and working time…).

The results show the added value provided by the holistic modelling approach of the biologic and economic processes. Three key characteristics of the model are highlighted: it (i) allows a broad range of possible solutions (no *a priori*), (ii) offers a good equilibrium and ponderation within the precision level of the modelling and (iii) has a real optimisation tool for the economic modelling. Many models used up to now do not fulfill these criteria, and biased conclusions may result from these models. This issue is the most challenging for PLF since the questions raised are very specific and focused. For precision livestock farming, this kind of approach gathering high level of resolution in the modelling process and holistic system approach may be of interest (i) for the algorithm itself as a tool to help decision making and event prediction, and (ii) for the economic evaluation of PFL new technology (cost and added value of the new technology output).

Keywords: Animal health economics, bio-economic modelling, mathematical programming, mastitis

Introduction

Economic approaches on disease management has been developed to help defining health standards and decision rationale. Micro-economics of production diseases is particularly challenging from a methodological point of view, especially for cattle production in most of livestock systems, due to (i) the high complexity of the production function linked to an open production system with high variability and difficulties to measure inputs/outputs, (ii) the long to very long time pattern (2 years to start milk production, half turnover of five years), and (iii) a series of daily decisions made on various topics by individuals or a small group of farmers.

Livestock farming represents a complex biological system where farmer has to continuously make decisions under many constraints (animal welfare, antimicrobial use, price volatility…). It appears that precision livestock farming and micro-economics of farm production have close needs and both require an holistic approach (due to the system-based organisation of the process studied), allowing at the same time a very high level of modelling resolution, since the question we want to answer is very specific. For precision livestock farming, this kind of approach gathering high level of resolution in the modelling process and holistic system approach may be of interest (i) for the algorithm

for itself as a tool to help decision making and event prediction, and (ii) for the economic evaluation of PFL new technology (cost and added value of the new technology output).

For this purpose, considering revenue as the only component of farmer's utility does not seem still acceptable. Moreover, risk aversion, workload and anticipation of market changes appear as key criteria to be included. Societal pressure on farming characteristics are increasing continuously, and animal welfare or antimicrobial use are key criteria to be included in evaluations.

We aim here to propose a new bio-economic stochastic sequential modelling of dairy production to show the added value of multicriteria decision in farming process.

Material and methods

A bio-economic model was developed to analyse the trade-offs between AMU and farm income in dairy cattle production. First, a biologic model defined on a cow-week basis and weekly probabilities of events, productions and diseases was implemented using R statistical software. This biological component aims at the dynamic representation of a dairy herd. It allows to formulate and simulate livestock management scenarios and build an input and output matrix for each scenario. The biologic model was then combined with an economic optimisation model implemented using General Algebraic Modelling System (GAMS) software. The economic model aims at maximising the farmer's risk-adjusted income under budget, working time, AMU and animal welfare constraints.

The bio-economic model was calibrated based on literature review and experts' opinions. The model was run over 10 years and includes sequentially the most common potential decision and management strategies by the farmer.

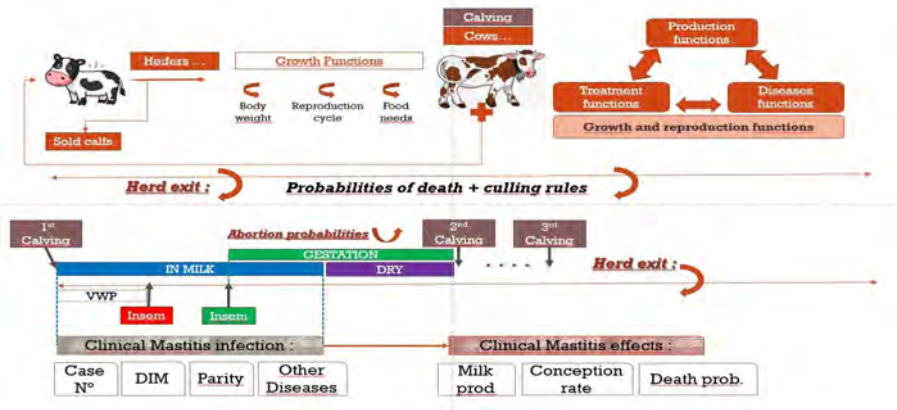


Figure 1. Bio-economic model representation

Economic model overview

The economic model developed is a recursive mean-variance optimisation framework which assumes that farmers make their decisions in order to maximise their income while minimising the associated risk, under technical, biological, structural and AMU constraints. We assume that farmers are risk-minimisers since many studies have demonstrated that they are typically risk-averse. This means that they are willing to sacrifice a part of their income to avoid facing risk. To incorporate risk-averse behaviour in farmers' decision making, we use a Markowitz-Freund mean-variance objective function. Mathematically, the economic model can be formulated as follows (equations 1 - 8):

$$\max \boldsymbol{F} = E[Z_{k,t}] - \frac{1}{2}\phi\sigma(Z_{k,t}) \quad (1)$$

$$\boldsymbol{Z_{k,t}} = \sum_l (MilkProd_{l,t} \times MilkPrice_{l,k,t}) + \sum_a (NS_{a,t} \times SalePrice_{a,k,t}) - \sum_{a,co} (N_{a,t} \times ConcQty_{co,t} \times ConcPrice_{co,k,t}) - \sum_{a,F} (N_{a,t} \times MedQty_{F,t} \times MedPrice_{F,t}) - \sum_v (Vet_{v,t} \times VetCPrice_{v,t}) \quad (2)$$

$$\boldsymbol{E[Z_{k,t}]} = \frac{\sum_k Z_{k,t}}{K} \quad (3)$$

$$(\boldsymbol{Z_{k,t}}) = \sqrt{\frac{(Z_{k,t} - E[Z_{k,t}])^2}{K}} \quad (4)$$

Equation (1) denotes objective function of farmers where E denotes expected values, ***k*** represents the state of nature which is defined here as the possible level of price; $Z_{k,t}$ stands for the income generated per state of nature ***k*** in year ***t***, ϕ is the risk aversion coefficient, and $\sigma(Z_{k,t})$ is the standard-deviation of the income. Equation (2) indicates how the income is computed. In this expression, $\boldsymbol{MilkProd}_{l,t}$ denotes the milk of type ***l*** sold at time ***t***; the type of milk is linked to number of cellules in case mastitis, $\boldsymbol{MilkPrice}_{l,k,t}$ represents the price of the milk of the type l sold in state of nature ***k*** at time ***t*** ;$\boldsymbol{NS}_{a,t}$ denotes the number of animals of type a (dairy cows, heifers and calves) sold at time ***t***; $\boldsymbol{SalePrice}_{a,k,t}$ is the price of animals of type a sold in the state of nature ***k*** at time ***t***. The sales price of the cull cows includes a slaughter premium. $\boldsymbol{ConcQty}_{co,t}$ indicates the quantity of each type of purchased food co (soybean meal, rapeseed meal, wheat, and milk powder) ingested at time t; $\boldsymbol{ConcPricec}_{o,k,t}$ stands for the prices of each type of purchased food in the state of nature ***k*** at time ***t***. $\boldsymbol{N}_{a,t}$ stands for the number of animals of type a at time t; $\boldsymbol{MedQty}_{F,t}$ indicates the quantity of drugs of type F used at time ***t*** and $Vet_{v,t}$ indicates veterinary interventions of nature ***v*** at time ***t***. Equation (3) indicates how to compute the expected value of the income, and equation (4) indicates how to compute its standard deviation.

Biologic model overview

The biological model aims at the dynamic representation of dairy herd growth. The biological model simulated herd's population, cow reproduction, milk production and health on the basis of cow-week events defined by a matrix of probabilities.

We consider in this model the dynamic interaction between livestock production, damage and damage control functions. The trio of functions also interact with growth and reproduction functions and drives the herd exit functions (culling, death and sell).

It aims to be as exhaustive as possible to represent all the practical cow-related events of the farm, including production and diseases.

It included all categories of animals from birth to death or culling and all the physiological states of animals (dry, in milk, open, in calf…). The events were defined for each cow and each week mechanistically, based on basic incidences, cow specific risk factors and herd contamination risks.

The cow's diseases included lame, dystocia, milk fever, placental retention, pueperal metritis, purulent vaginal discharge, subclinical endométritis, left + right abomasum displacement, subclinical ketosis, clinical ketosis and clinical mastitis (with six different pathogens); represented the high majority of disorders observed in dairy herds, except accident issue (broken leg …). The model also considers calves' diseases/troubles such as bovine viral diarrhea, septicemia, diarrhea, omphalitis, etc.

Culling rules were applied on all cows each week, with a series of criteria including udder health, lameness, pregnancy status and milk production, alone and in combination, so as to create a set of rules with increasing aggressivity in culling, applied in accordance to the herd density (i.e. the number of cows to be culled so as to maintain the herd size). The rules were

builds according to the observations made in the field so as to mimic the usual famer behaviour.

This algorithm structure allows us to precisely formulate and simulate many realistic livestock management scenarios and build an input and output matrix for each scenario.

Constraints and scenarios

Bioeconomic model constraints: The equation (1) will be estimated with the outcomes of the biological models and under the following technical, biological, structural and regulatory constraints.

First, the feeding constraints (Equation 5) were built so as to the sum of forage unit requirements (FUR) by animal category ***a*** and period ***p*** remains lower than or equal to the number of forage units available per period ***p,*** per crop ***c*** and concentrated feed ***co***.

$$\sum_a (N_{a,t} \times FUR_{a,p}) \leq \sum_c (X_{c,t} \times FU_{c,p}) + \sum_{co} (ConcQty_{co,p,t} \times FU_{co,p,t}) \quad (5)$$

The feeding system was based on three main components: corn silage, crop such as barley or wheat, and nitrogen corrective feed, such as soybean meal. Because the present model was herd centered and not farm centered, it was assumed that the quantity of corn silage to feed the hard was available each year. Its energetic value changes yearly due to weather growing conditions, and these changes have to be compensated by changes in concentrated food crops purchase.

Second, the workload constraints were considered as the sum of additional working time per strategy of disease management must be lower than a farmer's consent to work or available labour. The constraint labour time was implemented according to a monthly smooth rolling function considering monthly farmer's extra time available for health preventive and curative management as a fixed time value per week plus saved time on the previous weeks (below the average working time).

Third, the cash constraint was defined by Equation (6). It indicates that each year the available cash from the past year ($CASH_{t-1}$) and the revenue generated (REV_t) are used for disease management (DM_t), operational expenses ($OperCost_t$), household expenses ($HExp_t$) or saved ($CASH_t$). This equation ensures, in part, the "recursivity" of the model.

$$CASH_{t-1} + REV_t = DM_t + OperCost_t + HExp_t + CASH_t \quad (6)$$

Fourth, the constraint on AMU was built on the standardised exposition of animals to antimicrobial indicator ALEA (Animal Level of Exposure to AM). The constraint on ALEA was defined as a free constraint for scenarios where no reduction is simulated, and as a reduction constraint according to the baseline biological scenario ALEA outcomes.

Biological scenarios: The biological scenarios and the health management farmer's strategy were defined thanks to expert opinion and literature overview. The retained scenarios must (i) be in accordance with regulation in France (drug authorised), (ii) match with in the field common practices and (iii) have a given efficacy defined thanks to evidence-based medicine principles. Because each biological scenario included specific non-medical farm practices in addition to drug use, the scenario underlies farmer's state of mind and drug choice as well as overall farm management, leading to consider "health management strategy" adopted by farmer instead of biological scenarios alone. The different situations proposed here correspond to farmers' strategies under technical constraints.

The nine scenarios were defined as a combination of three scenarios representing technical strategies related to clinical mastitis management at dry-off (common practices and two alternatives) and three scenarios representing animal health management (common, deteriorated and adequate practices). Details are reported in Tables 1 and 2.

Table 1. Technical scenarios

	Description		Reference
T1: Common practice	Systematic treatment at dry-off	Reference risk	
T2: Alternative practice 1 at dry-off	Selective antimicrobial treatment at dry-off for cows > 150 000 scc	Odd ratio for risk of clinical mastitis up to 100 DIM = 2	(Scherpenzeel *et al.*, 2014)
T3: Alternative practice 2 at dry-off	Selective antimicrobial treatment at dry-off for cows > 150 000 scc and an internal teat sealer for other cows	The same risk as the reference technical scenario	(Crispie, Flynn, Ross, Hill & Meaney, 2004)

Table 2. Management scenarios definition

	Cleanliness at dry off	Cleanliness of in milk cows	Milking practices costs	Diet practices
M1 "Good" management scenario	5 kg of straw per cow per day	- 4 ~ 6 kg of straw per place per day - +0.20 min extra time per place. - odd ratio = 0.5 for probability of CM on 4 first WIM and for second and third cases on 8 first WIM	- 1 min extra time per cow - 0.0452 € extra cost per cow per day	5% of cows with risk factor for subclinical ketosis (change in practices during dry off)
M2: "common" management scenario	3 kg of straw per cow per day	- 3 ~ 5 kg of straw per place per day	Reference practices	15% of cows with risk factor for subclinical ketosis (change in practices during dry off)
M3: "deteriorated" management scenario	no straw	- 1.5 ~ 3 kg of straw per place per day - odd ratio= 2 for probability of CM on 4 first WIM and for second and third cases on 8 first WIM - 0.20 min saved time per place.	- 0.5 min saved time per cow	50% of cows with risk factor for subclinical ketosis (change in practices during dry off) - 30 min saved/ day for a 100 cows herd.

Calibration

The biological model developed here deals with quantitative data and facts with scientific backing. It is available on request to the authors.

Results and discussion

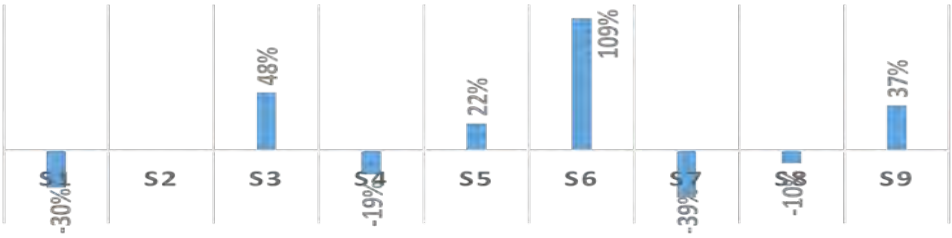
The results of nine scenarios are presented here. Details are proposed in Figure 1.

Simulations show that good management scenarios (S1, S4 et S7) allow to reduce antimicrobial treatments while maintaining farmers' economic profitability. However, those scenarios appear to be time-consuming. They are associated with a medium of 60 hours additional working time per month.

In 'usual' management scenarios context, systematic treatment (S2) and selective treatment associated to a teat sealant (S8) strategies shows similar mastitis infections and economic profitability levels. With the simple selective treatment strategy (S5), farmers' income is deteriorated mainly due to milk quality deterioration.

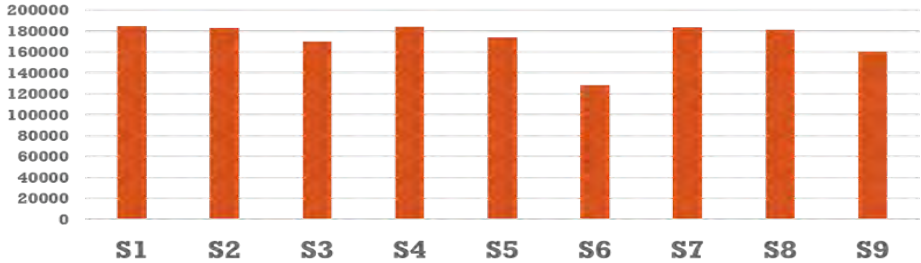
In bad breeding practices (S3, S6 and S9), systematic treatment makes it possible to secure the income of the farmer, with a limited reduction of the risky income (S3).

A-Exposition to antimicrobials (% of change compared to S2)



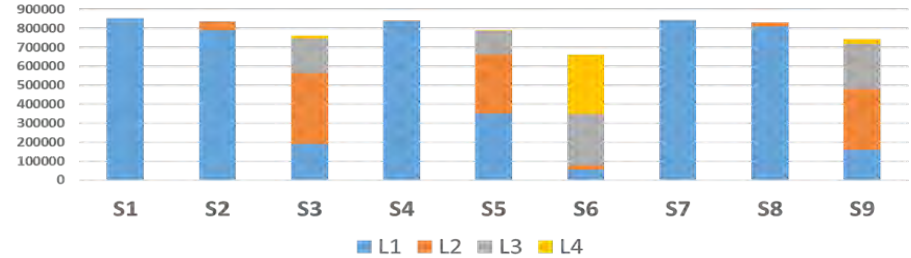
S1 : T1M1 ; S2 = T1M2 ; S3= T1M3 ; S4 : T2M1 ; S5 = T2M2 ; S6= T2M3 ; S7 : T3 M1 ; S8 = T3M2 ; S9= T3M3

B -Expected utility (€ / year)



S1 : T1M1 ; S2 = T1M2 ; S3= T1M3 ; S4 : T2M1 ; S5 = T2M2 ; S6= T2M3 ; S7 : T3 M1 ; S8 = T3M2 ; S9= T3M3

B – Milk produced / year



S1 : T1M1 ; S2 = T1M2 ; S3= T1M3 ; S4 : T2M1 ; S5 = T2M2 ; S6= T2M3 ; S7 : T3 M1 ; S8 = T3M2 ; S9= T3M3

L1 : Bulk milk with SCC < 250 000 cells/mL, L2 : Bulk milk with SCC = 250 000-300 000 cells /mL, L3 : Bulk milk with SCC = 300 000-400 000 cells /mL, L2 : Bulk milk with SCC > 400 000 cells /mL

Figure 2. Results of the models

Three main empirical results are highlighted here. First, a decrease in the use of antimicrobials is possible, with marginal cost that is low to zero, in some situations with good health practices. Second, the antimicrobial use reduction is more problematic in deteriorated farming conditions and these practice changes represents a significant labour investment. Third, the existence of a therapeutic alternative makes it possible to secure the income of certain breeders with 'usual' health practices.

The bioeconomic model we propose here go beyond most of the models proposed in literature. It is of high interest for PFL for at least three reasons.

First, the biologic part of the models appears as 'closed' in most of the models in literature. Closed refers to the fact that they include many *a priori*: all the fields of possibilities are not reachable by the models, limiting thereafter the search of optimal solutions. Typical examples in dairy production include culling (with several causes), death and heifer availability. The present model is mechanistic and aims to include no exogenous *a priori*. This is a key point for PLF since the prediction of a new event for a cow or of the herd characteristic evolution may be biased in cases of partial approach or strong *a priori*. The simulation of the reform in the model is based on the evaluation of the cow's condition in comparison with rules set at the beginning of the model, in three main axes: production performances (quantity and quality of the milk), reproduction and health status (including lame). Results showed that for scenarios with high clinical mastitis prevalence, culling rules for udder health and milk quality (somatic cell counts) are the most applied rules.

Second, the model proposes an algorithm that accurately and realistically represents biological and livestock management processes: the algorithm reproduces field situations in a very close way, what allows to simulate a large number of scenarios focused on 'hot spots' of dairy cattle farming.

Last but not least, the present model allows an optimisation process using multicriteria consideration. Compared to scenario M2, scenario M1 lead to + 60 h extra labour and the scenario M3 30 h less labour per month, including labour time within the optimisation process leading to a very different optimal decision. This is of high concern for precision farming since reducing labour time is often a key criterion to adopt PLF technology.

Conclusions

We propose a new bio-economic stochastic sequential modelling of dairy production that allows multicriteria decisions to be made in farming process. We showed that this kind of approach gathering high level of resolution in the modelling process and holistic system focus brings added value for decision making and goes beyond the existing models. These kind of methods are currently becoming the standards in economics applied to animal health. They add value for PFL by themselves with the algorithm used to help decision making and to predict events, and for the economic evaluation of PFL new technology.

Acknowledgements

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References

Crispie, F., Flynn, J., Ross, R.P., Hill, C., & Meaney, W.J. (2004). Dry cow therapy with a non-antibiotic intramammary teat seal - a review. *Irish Veterinary Journal*, 57(7): 412. https://doi.org/10.1186/2046-0481-57-7–412.

Scherpenzeel, C.G.M., den Uijl, I.E.M., van Schaik, G., Olde Riekerink, R.G.M., Keurentjes, J.M., & Lam, T.J.G.M. (2014). Evaluation of the use of dry cow antibiotics in low somatic cell count cows. *Journal of Dairy Science*, 97(6): 3606–3614. https://doi.org/10.3168/jds.2013–7655.

The extensive literature used for calibration is not reported here. Available upon request to authors.

Monitoring standing and lying behaviour of dairy cows at pasture under different grazing management plans

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Abstract

Our objective was to examine differences in dairy cow standing and lying behaviour patterns across different grazing management plans that varied in pasture supply and management intensity. We hypothesized that cows in a higher pressure grazing system, with reduced pasture availability and higher competition, would display greater standing times and reduced lying behaviour. Ten focal cows were selected from each of three spring grazing management plans, balanced for breed, parity and body weight. Treatments represented low pressure (LOW; 1,100 kg DM/ha grass available at calving, 2.75 cows/ha and 90% pasture diet), moderate pressure (MOD; 900 kg DM/ha grass available at calving, 2.75 cows/ha and 90% pasture diet), and high pressure (HIGH; 700 kg DM/ha grass available at calving, 3.25 cows/ha and 80% pasture diet) grazing plans. Groups were monitored from March - May 2018. Daily standing time, lying time, and lying bout and step frequency data were collected using accelerometers secured to the rear leg of each cow. Data from three, 10 d periods corresponding to the Early, Mid and Late spring grazing season were summarised by cow, day, treatment and period, and analysed for differences in behaviour. HIGH pressure cows tended to have reduced lying time and greater standing times ($P = 0.07$). Grazing period significantly influenced standing and lying time ($P = 0.02$), with a decrease in standing time and increase in lying time from Early to Late spring grazing. Additionally, lying bout frequency decreased while step frequency increased over the grazing period ($P < 0.001$).

Keywords: lying behaviour, dairy cows, grazing management

Introduction

Irish pasture-based dairy systems have undergone a shift towards increased herd sizes and greater milk production per hectare in recent years due to the elimination of production quotas (CSO, 2017). Ensuring efficient pasture management is a key factor in sustaining continued growth in the Irish dairy industry, which is based on a cow's ability to convert grass to milk solids with minimal inputs to the system. Thus, much research has focused on promoting high quality swards and greater productivity through greater stocking rate (SR: the number of cows per unit of land, e.g. cows/ha) (McCarthy *et al.*, 2013, Baudracco *et al.*, 2010 and McDonald *et al.*, 2008), and optimum herbage allowance (Stakelum and Dillon, 2007, Maher *et al.*, 2003). However, higher intensity grazing systems (those with low pasture availability and high stocking rates) may increase the pressure on grazing cows to meet daily nutritional requirements. This may impact their productivity and welfare, as more time spent grazing to meet energy demands may have a negative effect on daily lying time. Lying time is known to be an important, high priority, behaviour in a cow's daily time budget (Krohn and Munksgaard, 1993; Munksgaard *et al.*, 2005) with cows spending approximately 9 - 11 hrs/d lying down at pasture (Hernandez-Mendo *et al.*, 2007, O'Driscoll *et al.*, 2015). Thus, sufficient lying time is considered an important indicator of good dairy cow welfare (Whay *et al.*, 2003). Reduced pasture allowance has been shown to result in fewer but longer lying bouts, and a longer latency to lie down after milking, potentially indicating feelings of hunger that are driving longer grazing periods (O'Driscoll *et al.*,

2015). The objective of this study was to examine differences in dairy cow standing and lying behaviour under grazing management plans that varied in pasture availability and grazing intensity. We hypothesized that cows under higher grazing pressure, would display greater standing times and reduced lying behaviour.

Materials and methods

Holstein Friesian (HF) and HF × Jersey cows (n = 30) were selected from an existing study (n = 144) of the effect of grazing management on dairy production. From each of three different treatment groups, 10 focal cows were chosen, balancing for breed, parity and body weight. The treatments were:

- *Low grazing pressure (LOW):* 1100 kg DM/ha grass available at spring calving, stocking rate of 2.75 cows/ha and a 90:10% pasture: concentrate diet
- *Moderate grazing pressure (MOD):* 900 kg DM/ha grass available at spring calving, stocking rate of 2.75 cows/ha and a 90:10% pasture: concentrate diet
- *High grazing pressure (HIGH):* 700 kg DM/ha grass available at spring calving, stocking rate of 3.25 cows/ha and a 80:20% pasture: concentrate diet

All cows were enrolled in their treatment groups and turned out to pasture at calving. Focal cows in each group were managed in the same manner as all other cows within the group. All focal cows were monitored 24 hrs/d for 11 weeks during the spring grazing period from March - May 2018, both while at pasture and during periods of housing.

To monitor standing and lying behaviour, an accelerometer leg-band (IceTag; IceRobotics Ltd., Edinburgh, Scotland, U.K.) was secured to a rear leg, below the hock, of each focal cow at the start of data recording. The IceTags remained in place for the duration of the study, removing them only once after approximately six weeks, when data download was required. The IceTag accelerometer recorded the daily standing and lying time, step frequency and number of lying bouts (number of times a cow lay down for an interval > 4 min). The IceTags were removed from all cows at the end of the study period. Resulting data was downloaded using the IceManager program (IceRobotics Ltd., Edinburgh, Scotland, U.K.) in hrs/d for each behaviour, then summarised by cow, treatment and period in SAS 9.4 (SAS Institute Inc., 2014).

From the data, three 10 d periods were identified that represented distinct stages of the 2018 spring grazing season; Early (mean DIM = 30 ± 9, all treatment groups indoors for partial days except the Low group), Mid (mean DIM = 69 ± 9, all treatment groups out by day only) and Late (mean DIM = 94 ± 9, all groups out full time) spring grazing periods. Summarised data for each outcome variable (standing time, lying time, step frequency and number of lying bouts) were analysed using a general linear mixed model, using the GLIMMIX procedure to determine differences between treatments. Fixed effects were treatment, period and the interaction of treatment with period; cow was the random effect and period was modelled as a repeated measure with an Autoregressive(1) covariance structure. All values were reported as least square means and significance was declared at a level of $P < 0.05$. Residuals were examined to ensure all assumptions of normality were met.

Results and discussion

In the current study there was a tendency for cows in the HIGH treatment group to spend the most time standing and least time lying down ($P = 0.07$) whereby HIGH cows lay down for 2 hrs/d less than LOW cows (HIGH = 9.1hr/d, LOW = 11.1hr/d). This suggests that under more intense grazing management, cows are spending more time grazing in order to satisfy their daily nutritional requirements, rather than resting. This is potentially

detrimental to dairy cow welfare, as restricted lying time can induce a physiological stress response in lactating dairy cows (Fisher *et al.*, 2002). Despite this, there was no observed difference in the number of lying bouts across treatments, suggesting that cows in the LOW treatment group lay down for a longer duration each time compared with cows in the HIGH treatment group. This is contrary to research by O'Driscoll *et al.* (2015) who found cows with higher daily pasture allowances had shorter bouts of lying time than cows with lower. However, in the current study, cows were housed indoors for part of each day during the early spring period, while the latter looked at cows at pasture full-time, which may have influenced the cows' lying behaviour.

Cows across all treatments spent significantly less time lying down and more time standing during the Early spring grazing period than during Late spring grazing (Early = 9.5 hrs lying/cow/d & 14.5 hrs standing/cow/d, Late = 10.8 hrs lying/cow/d & 13.2 hrs standing/cow/d, $P = 0.02$). Cooler and wetter early spring weather may play a role in this behaviour, as cows without shelter show longer standing times during poor weather conditions (Tucker *et al.*, 2007). Cows also displayed significantly more lying bouts during the Early period (Early = 11 bouts/cow/d, Late = 8 bouts/cow/d, $P < 0.01$), an indicator of more restless behaviour than later in the season. These differences in behaviour may be due to lower grass growth and availability earlier in the season, that requires longer grazing time to meet the energy demands of cows approaching their peak production. In seasonal pasture-based systems such as the current study, cows are also in early lactation during the Early spring grazing period, which has been associated with reduced lying times (Maselyne *et al.*, 2017). In addition, cows spent a greater amount of time in indoor housing during the Early period due to adverse weather and so the lower lying time and more lying bouts may also suggest discomfort in the indoor housing environment resulting in more restless lying behaviour. Similarly, O'Connell *et al.*, (1989), found that pasture-based dairy cows displayed more restless behaviour when housed indoors, with 50% fewer cows laying down simultaneously overnight compared to when they were at pasture.

The step frequency of each cow was examined as an indicator of activity level while standing, and we found no effect of treatment. In contrast, period was significant for step frequency, with increased activity shown by all groups during the Mid and Late spring periods (Early = 2,415 steps/cow/d, Mid = 3,635 steps/cow/d, Late = 3,811 steps/cow/d, $P < 0.01$). The increase in step frequency may be related to stage of lactation, as cows show lower step frequency and lying times in the first month after calving (Maselyne *et al.*, 2017). It was speculated that this may be related to udder discomfort caused by increasing milk production in the weeks following calving (Osterman and Redbo, 2001) or due to greater feeding time to meet nutritional demands (Løvendahl and Munksgaard, 2016). However, further research is required to understand this pattern of behaviour. In conjunction with reduced access to pasture during early spring due to poor weather conditions, and therefore less grazing-driven activity, this may explain the significantly lower step frequency in Early versus Mid and Late spring grazing periods.

Conclusions

Grazing management treatment tended to influence standing and lying behaviour in grazing cows, which lends support to our hypothesis that in the higher pressure system, characterised by lower pasture availability and a more intense farm system, cows would display reduced lying time and more standing time than the lower pressure system. However, period of the grazing season was also found to play a large role in the pattern of lying behaviour in grazing dairy cows; potentially due to changes in stage of lactation and access to pasture.

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References

Baudracco, J., Lopez-Villalobos, N., Holmes, C.W., Macdonald, K.A. (2010). Effects of stocking rate, supplementation, genetic strain and their interactions on grazing dairy systems: a review. *New Zealand Journal of Agricultural Research,* 53: 109–133.

Central Statistics Office. Livestock Survey December. (2017). https://www.cso.ie/en/releasesandpublications/er/lsd/livestocksurveydecember2017/.

Fisher, A.D., Verkerk, G.A., Morrow, C.J. and Matthews, L.R. (2002). The effects of feed restriction and lying deprivation on pituitary-adrenal axis regulation in lactating cows. *Livestock Production Science,* 73: 255–263.

Hernandez-Mendo, O., von Keyserlingk, M.A.G., Veira, D.M. and Weary, D.M. (2007). Effects of pasture on lameness in dairy cows. *Journal of Dairy Science*, 90: 1209–1214.

Krohn, C.C. and Munksgaard, L. (1993). Behaviour of dairy-cows kept in extensive (loose housing pasture) or intensive (tie stall) environments. 2. Lying and lying- down behaviour. *Applied Animal Behaviour Science*, 37: 1–16.

Løvendahl, P., Munksgaard, L. (2016). An investigation into genetic and phenotypic variation in time budgets and yield of dairy cows. *Journal of Dairy Science*, 99: 408–417.

McCarthy B., Delaby, L., Pierce, K.M., Brennan, A., and Horan, B. (2013). The effect of stocking rate and calving date on milk production of Holstein-Friesian dairy cows. *Livestock Science,* 153, 123–134.

Macdonald, K.A., Penno, J.W., Lancaster, J.A.S., and Roche, J.R. (2008). Effect of stocking rate on pasture production, milk production and reproduction of dairy cows in pasture-based systems. *Journal of Dairy Science*, 91:2151–2163.

Maher, J., Stakelum, G., and Rath, M. (2003). Effect of daily herbage allowance on the performance of spring-calving dairy cows. *Irish Journal* of *Agricultural* & *Food Research*, 42, 229–241.

Maselyne, J., Pastell, M., Thomsen, P.T., Thorup, V.M., Hänninen, L., Vangeyte, J., Van Nuffel, A. and Munksgaard, L. (2017). Daily lying time, motion index and step frequency in dairy cows change throughout lactation. *Research in Veterinary Science*, 110: 1–3.

Munksgaard, L., Jensen, M.B., Pedersen, L.J., Hansen, S.W., and Matthews, L. (2005). Quantifying behavioural priorities—effects of time constraints on behaviour of dairy cows, *Bos Taurus*. *Applied Animal Behaviour Science.* 92, 3–14.

O'Connell, J., Giller, P.S., Meaney, W. (1989). A comparison of dairy cattle behavioural patterns at pasture and during confinement. *Irish Journal* of *Agricultural* & *Food Research,* 28(1): 65–72.

O'Driscoll, K., Lewis, E., and Kennedy, E. (2015). Effect of feed allowance at pasture on lying behaviour and locomotory ability of dairy cows. *Applied Animal Behaviour Science*, 166: 25–34.

Österman, S., Redbo, I. (2001). Effects of milking frequency on lying down and getting up behaviour in dairy cows. *Applied Animal Behaviour Science*, 70: 167–176.

Stakelum, G., and Dillon, P. (2007). The effect of grazing pressure on rotationally grazed pastures in spring/early summer on subsequent sward characteristics. *Irish Journal* of *Agricultural* & *Food Research,* 46: 15–28.

Tucker, C.B., Rogers, A.R., Verkerk, G.A., Kendall, P.E., Webster, J.R., Matthews, L.R. (2007). Effects of shelter and body condition on the behaviour and physiology of dairy cattle in winter. *Applied Animal Behaviour Science*, 105: 1–13.

Whay, H.R., Main, D.C.J., Green, L.E., and Webster, A.J.F. (2003). Animal-based measures for the assessment of welfare state of dairy cattle, pigs and laying hens: Consensus of expert opinion. *Animal Welfare*, 12: 205–217.

Combining automatic feeding records and image analyses to study feeder occupancy in growing-finishing pigs

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Abstract

Automatic feed intake recording systems are used in growing-finishing pigs to estimate individual feed conversion efficiency and to quantify feeding behaviour. Moreover, these systems could allow inferring competition for a single feeder space in the form of multiple pig occupancy of a feeder during short periods of time. The goal of this study was to use automatic image classification to infer single pig and multiple pig occupancy of feeders and to contrast the results to those obtained from automatic feeder data. Top-down images of a feeder were collected every four seconds for three consecutive days. A total of 652 manually classified images were used to train a feed-forward artificial neural network for image classification. Over 64,000 images were classified using the trained model and 1,000 randomly chosen images from each feeder occupancy outcome (empty, single pig, multiple pigs) were selected for validation. Accuracy was 100% for images labelled as empty feeder, 99% for image classified as single pig (1% were images with two pigs) and 90% for images classified as multiple pigs (10% were single pig). Image timestamps were used to assign 64,000 classified images to 276 automatic feeder event data. 95% of feeding records with outlying high weights corresponded to a feeder that was occupied by more than one pig at least 24% of the time. While in events leading to normal weight records, 90% of the events had more than one pig in the feeder for less than 24% of the time. These results indicate a correlation between extreme high weight records and multiple pig occupancy of single space feeders, but the correlation is not strong enough to accurately classify events based solely on automatic feeding records.

Keywords: automatic feeders, image classification, pigs

Introduction

Automatic feed intake recording systems are used in growing-finishing pigs to estimate individual feed conversion efficiency and to quantify feeding behaviour (Lu *et al.*, 2017). For instance, the number of visits per day, time of visit, length of visit, amount consumed and pig weight (if the feeder is equipped with a scale platform) in each visit are recorded with this type of device. However, there are potentially other measures or variables that could be recorded or inferred from automatic feeding stations. Of particular interest is the use of automatic feeding records to infer competition between pen mates. Competition could be detected in single-space automatic feeders through flagging simultaneous occupancy of a single space feeder by multiple pigs. Another way to detect competition for feeder space at the group level could be by tracking the amount of time that a feeder is empty vs occupied, especially during normal feeding hours (daylight hours of the cycle inside the barn). Moreover, when the feeder is equipped with a scale, it is not uncommon to observe anomalous high or low weights of the visiting pigs, that could flag multiple pig occupancy events. However, the use of feeders for the purpose of evaluating competition among pigs has not been tested or compared to a reference method.

Another way in which feeder occupancy could be tracked is through recording video or taking pictures of the feeder and then sorting the frames into categories such as: empty feeder, feeder occupied by a single pig or feeder occupied by multiple pigs. However,

manually classifying pictures or annotating video frame by frame is a tedious task that could be automated utilizing a computer algorithm.

The goals of this study were: 1) To implement and test an automatic image classification algorithm to detect single pig and multiple pig occupancy of single space feeders and 2) To contrast the results obtained with the image classification algorithm to automatic feeder records.

Material and methods

Experimental animals

A total of 12 purebred Yorkshire gilts were housed in a single pen (pen dimension: 4.8 meters by 2.4 meters). The pen dimensions and stocking rates are typical of the MSU swine teaching and research centre and of other commercial growing-finishing facilities in the US. Pigs were approximately 84 ± 4 days old and their average weight was 41.3 kg ± 7.67 kg.

Images collection and pre-processing

Pictures were taken with an Intel® RealSense™ D435 camera using modified Intel® RealSense™ SDK 2.0 source code to capture top-down depth images of the feeder area approximately every 3.5 seconds for approximately 66 consecutive hours. A total of 64,840 images were taken and saved in timestamped files. A preliminary test was performed comparing the quality of depth images and digital images, and only depth images were utilised for this study. After image collection, the region of interest was cropped, resized to 154 by 49 pixels, and stored for further analysis.

Feeder data

Feeder records were collected using a single-space Feed Intake Recording Equipment (FIRE) feeder (Osborne Industries, Inc., Osborne, KS). The FIRE feeder was equipped with a weighing scale (ACCU-ARM Weigh Race; Osborne Industries Inc., Osborne, KS) to measure the live weight of the pig (or pigs) trying to access the feeder. The data stream produced by the FIRE feeder included: 1) the ID of the animal, obtained by reading an RFID tag located in the right ear of the pig; 2) the start and end time of the feeding event; 3) the total feed consumed during the feeding event; and 4) the weight of the pig during the feeding event. The automatic feeder dataset collected data over the 66 hours of the experiment and included a total of 276 feeding records.

Image classification

A two-step prediction protocol was built using two binary classifications models. The first model classified images as "empty feeder" or "occupied feeder", and the second model classified images from the occupied feeder category into "single pig occupancy" or "multiple pig occupancy". Both models consisted of a four-layer feed forward neural network (LeCun *et al.,* 2015). The first layer had 512 nodes, the second layer had 256 nodes and the third layer had 64 nodes. The activation function for the first three layers was ReLU (Rectified linear unit). The last layer had two nodes and its activation function was Softmax. 652 images were manually labelled as "empty feeder" (N = 205), "single pig occupancy" (N = 336) or "multiple pig occupancy" (N = 111) to train the models. After the models were trained, the remainder of the 64,860 images were classified, and a random sample of 1,000 images was extracted for manual classification and validation. All analyses were performed using NVIDIA CUDA v9.0 development tools coupled with the tensorflow and keras packages of R (Team 2013), enabling fast GPU computing.

Receiver operating characteristics of image classifiers

Accuracy, Specificity and Sensitivity (Parikh *et al.*, 2008) of each model were estimated assuming that the "positive" event was to detect exactly one pig in the feeder. Thus, for

model 1, the "negative" event was to detect an empty feeder and for model 2, the "negative" event was to detect multiple pigs inside the feeder space. Consequently, the formulae for receiving operating characteristics in each model were:

$$\text{Sensitivity}_{\text{Model 1}} = \frac{\text{\#correctly classified images as occupied feeder}}{\text{\#images of occupied feeders}} \quad (1)$$

$$\text{Specificity}_{\text{Model 1}} = \frac{\text{\#correctly classified images as empty feeder}}{\text{\#images of empty feeders}} \quad (2)$$

$$\text{Accuracy}_{\text{Model 1}} = \frac{\text{\#correctly classified images}}{\text{\#images}} \quad (3)$$

$$\text{Sensitivity}_{\text{Model 2}} = \frac{\text{\#correctly classified images as single pig occupancy}}{\text{\#images of single pig occupancy}} \quad (4)$$

$$\text{Specificity}_{\text{Model 2}} = \frac{\text{\#correctly classified images as multiple pig occupancy}}{\text{\#images of multiple pig occupancy}} \quad (5)$$

$$\text{Accuracy}_{\text{Model 3}} = \frac{\text{\#correctly classified images as occupied feeder}}{\text{\#images of occupied feeders}} \quad (6)$$

Synchronization of automatic feeding data stream and image data stream

Before the start of the recording experiment, the clocks of the FIRE feeder and the clock of the computer used for image recording were manually synchronized to within 1 second of each other. After the 66-hour recording experiment, the synchronization of the clocks was verified again. Consequently, the timestamp of each image and the timestamps of the feeding events could be compared and used for alignment of images to feeding records.

Flagging of outlying weights in automatic feeder data

For each animal in the experiment, an individual growth curve was estimated based on previous weight records. A quantile regression (Koenker, 2005) was used to estimate quartiles of the growth curves that were robust to outliers. Subsequently, high weight outliers with respect to the median growth curve were flagged for weight records that were larger than the third quartile of the predicted weight plus three times the inter quartile range of the distribution of predicted weights at the days of the trial (Tukey, 1977). All statistics were computed individually for each animal in the trial to account for animal-specific weight growth curves.

Occupancy index of a feeding event

An occupancy index (OI) for each feeding event was computing using images of the feeder corresponding to the time-span of the event.

$$\text{OI} = \frac{\text{\# single pig images} + 2 \times \text{\#multiple pig images}}{\text{total \# of images in the event}} \quad (7)$$

In this index it was assumed that multiple pig occupancy always involved two pigs. The assumption was validated by manually checking over 200 feeder images with more than one pig in it.

Results and discussion

Receiver operating characteristics of image classifiers

Image classification was extremely fast once models were trained. For instance, using GPU computing, almost 65,000 images were classified in approximately 40 seconds. Model 1 (classifying images as empty feeders vs occupied feeders) had an Accuracy of 99% (proportion of correctly classified images), Sensitivity of 99% (proportion of correctly classified empty feeders) and Specificity of 98% (proportion of correctly classified occupied feeders). Model 2 (classifying images of feeders occupied by a single pig vs feeders occupied by multiple pigs) had Accuracy equal to 98.1%, Sensitivity equal to 98.9% and Specificity equal to 90%. The lower specificity indicates that 10% of the images of feeders classified as occupied by multiple pigs by Model 2 corresponded instead to single pig occupancies.

Feeder occupancy

Estimated feeder occupancy was 85% regardless of the method (image analysis or FIRE feeder data). The two methods agreed in detecting overall feeder occupancy (occupied vs empty) 96% of the time (Figure 1). This value is only slightly lower than the accuracy, specificity and sensitivity of Model 1 for classifying images between empty and occupied feeders. Moreover, using image classification we could also detect, although with lower specificity (90%), multiple pig occupancy of feeders.

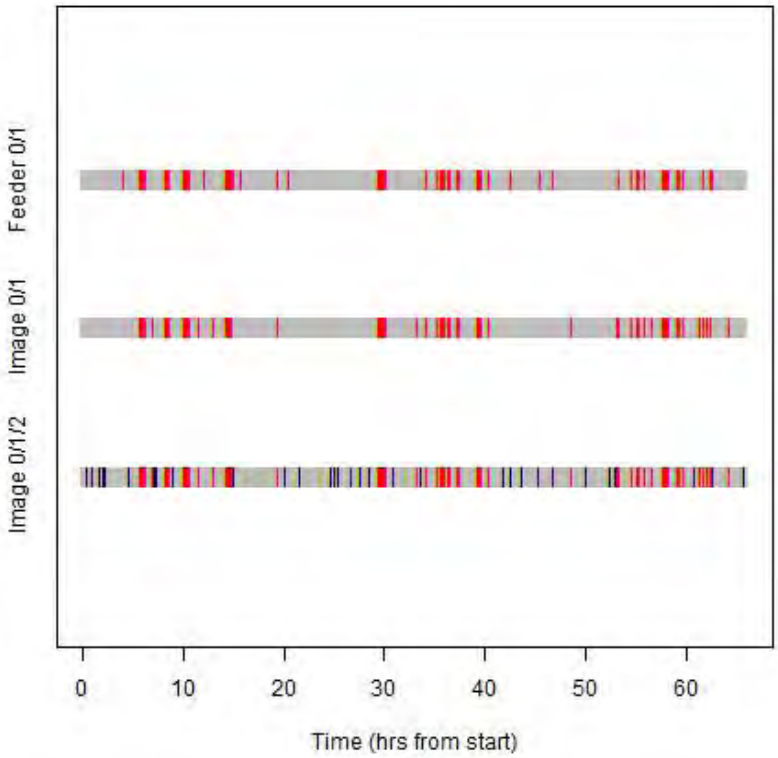

Figure 1. Feeder occupancy over the course of the experiment (horizontal axis), as estimated by: 1) FIRE Feeder data stream (Feeder 0/1), 2) Model 1 for image classification (Image 0/1) and 3) Model 1 + Model 2 for image classification (Image 0/1/2). A red bar indicates an empty feeder, a grey or black bar indicates an occupied feeder, a black bar indicates a feeder occupied by more than one pig

Feeder weight records and feeder occupancy

In order to investigate the potential of using the weight records from automatic feeder data to detect multiple pig occupancy of the feeder, we selected automatic feeder records that were flagged for outlying high weights (22 out of 276 records) and computed an occupancy index based on automatically classified images. The average occupancy index for feeding events with outlying high weights was 1.21 ± 0.35 while the average occupancy index for feeder events with non-extreme weights was 1.06 ± 0.15. Thus, although feeding events with extreme weight records tended to coincide with cases where a larger proportion of images were classified as multiple feed occupancy, the difference was not strong enough to use feeder data as the sole indicator of multiple pigs occupying the feeder space.

Conclusions

Image classification using feed forward deep neural networks can accurately detect occupied feeders. Predicting the number of animals in the feeder to detect competition for feeder space requires further work to increase beyond the current sensitivity of 90%. Real time application of these algorithms using GPU computing is feasible with a processing time of less than 1/100 of a second per image. The sole use of extreme weight records from automatic feeders to detect multiple pig occupancy does not seem feasible at this point.

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References

LeCun, Y., Bengio, Y., & Hinton, G. (2015). *Deep learning*. Nature, 521(7553), 436.

Lu, D., Jiao, S., Tiezzi, F., Knauer, M., Huang, Y., Gray, K.A., & Maltecca, C. (2017). *The relationship between different measures of feed efficiency and feeding behavior traits in Duroc pigs. Journal of Animal Science*, 95(8): 3370–3380.

Koenker, R. (2005). *Quantile regression*. Cambridge University Press New York.

Parikh, R., Mathai, A., Parikh, S., Sekhar, G.C., & Thomas, R. (2008). *Understanding and using sensitivity, specificity and predictive values*. *Indian journal of ophthalmology*, 56(1): 45.

Team, R.C. (2013). *R: A language and environment for statistical computing*.

Tukey, J.W.(1977). *Exploratory data analysis*. Reading: Addison-Wesley.

Effect of straw supply as environmental enrichment on skin surface temperature for prepartum sows

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Abstract

The research was conducted to evaluate the effects of environmental enrichment, using straw, on the superficial temperature (ST) of sows during prepartum, intrapartum and postpartum. Thirty-two sows were used (2nd to 8th birth orders). The animals were distributed according to the birth order in two treatments, with each sow being an experimental unit: 1) Control: sows in conventional farrowing crates without environmental enrichment; 2) Straw: supply of straw for nest construction as environmental enrichment in the conventional farrowing crates. The straw was offered in the crates through a wooden box fixed to the bars of the cages, at a height that allowed the animal to pick up the straw with the mouth. Surface temperature of the sows was obtained through infrared Thermovisor equipment at three moments: approximately six hours prepartum, during the partum and one hour postpartum. The mean surface temperature was calculated by the temperature of 30 points distributed to represent the overall body surface of the animals. The data were analysed using the SAS GLIMMIX procedure and submitted to Pearson's correlation ($P < 0.05$). There was a negative correlation between the birth order and the ST, indicating that younger sows presented a higher ST elevation during birth. There was no effect of straw supplying on ST in the evaluated periods, however, sows that spent more time on nest building presented lower ST. Sows housed in enriched crates showed signs of improvement in well-being, reducing the frequency of stereotyped behaviours and showed positive effects on the frequency of suckling.

Keywords: nest building, behaviour, birth order, thermography, welfare

Introduction

From the 1960's, pig farms adopted the housing system of sows in farrowing crates, in which the objective was to reduce piglet mortality, optimise facility space and facilitate human intervention during birth (Perdensen *et al.,* 2013). However, the use of these cages seriously compromises the welfare of the sows, due to the restriction of space and movements, as well as the lack of materials to build the nest in the prepartum period (Yun & Valros, 2015). The impossibility of constructing the nest before delivery favours the occurrence of stereotyped behaviours and increased stress (Lawrence *et al.*, 1994; Wischner *et al.,* 2009).

According to Vanheukelom *et al.* (2012), the farrowing crate differs substantially from the natural birthing environment of the sows in two aspects: restriction of movement due to lack of space and absence of suitable materials for nest building. Females housed in restrictive and sterile systems exhibit strong signs of frustration and restlessness, directing characteristic nesting activities to the floor, bars, and equipment of the cages. Therefore, the impossibility of building the nest before labour favours the appearance of stereotyped behaviour and increased stress (Wischner *et al.*, 2009).

Consequently, it becomes important to study strategies to provide materials for

nest building in farrowing crates, providing the opportunity for the sow to express natural maternal behaviour and in this way, improve their welfare. The use of infrared thermography consists of a non-invasive tool that can aid in the detection of animal stress in different situations (McManus *et al.*, 2016). In this context, the aim of this study was to evaluate the effects of environmental enrichment using straw in the prepartum period, on the surface temperature and welfare of sows before, during and after birth.

Material and methods

Animals, treatments and facilities

Twenty-two DanBred commercial sows were used and uniformly distributed according to birth order (2nd to 8th) in a completely randomized experimental design, with two treatments (control and straw) with 16 replicates, in which each sow was considered an experimental unit. In the control treatment, the females were kept in cages without environmental enrichment. In the straw treatment, 5.0 kg of the substrate (Tifton hay) was provided as environmental enrichment in the farrowing crates for the construction of the nest. In both treatments, conventional farrowing crates with suspended and fully slatted iron floor, spaced 0.016 m, with the following dimensions: 2.20 m long × 0.75 m wide corresponding to the area of the sow and 0.45 m wide relative to the escape area for the piglets.

Environmental enrichment

The straw was supplied through a wooden box made for this purpose. Each box had two openings: one at the top where the substrate was deposited inside and the other at the side, facing the sow, allowing the material to be manipulated by the animal. The boxes were attached by wires to the bars of the cages at a height that allowed the animal to pick up the straw with the mouth during the construction of the nest. Straw was offered around 24 hours before the expected date of delivery and taken the next day after giving birth.

Surface temperature and duration of nesting behavior

The surface temperature of the female pigs was obtained by the Termovisor Infrared Reporter (HT3, Hotec) at three times: approximately six hours before the expected onset of labour (determined from the time when the sow started to eject the colostrum), during birth and one hour postpartum (Figure 1). The thermography images were evaluated using the equipment specific software (IR Reporter V1.0.146), in which the colour spectrum reading was converted to surface temperature. The emissivity coefficient used was 0.96 for the entire body surface of the animal. The mean surface temperature and standard deviation of the body area were calculated by averaging 30 points uniformly distributed to represent the total body surface of the animals. To measure the duration of nest construction, the time of each characteristic nesting behaviour was registered to obtain the total duration in the evaluation period.

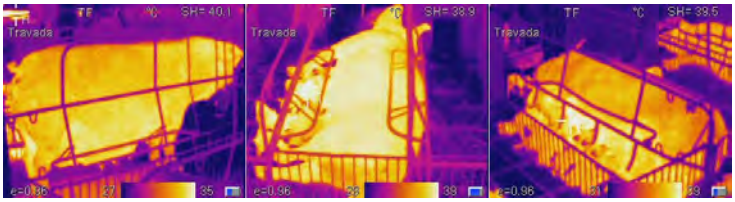

Figure 1. Surface temperature of the sows before (left image), during (middle image) and after delivery (right image)

Behavioural observations

The behavioural observations were carried out through the use of infrared cameras (ALT900W, Alartec) positioned above the farrowing crates, connected directly to a digital video recorder (CCTV DVR, Network H.264) and an LCD monitor (L1710, HP). The behaviours of 12 sows per treatment were recorded, without interruption (sampling of all occurrences), from 12 hours before the onset of labour until the 13th day of lactation. Behavioural assessments were divided into three periods (12 hours before delivery, during delivery and during 13 days postpartum) and categorised (Table 1) according to the behaviours described in adapted ethogram from Hansen *et al.* (2017). Stereotypies considered in ethogram were biting the cage and equipment.

Table 1. Behavioural repertoire before, during and after labour, and change of posture during delivery of sows housed in parental cells with or without environmental enrichment

	Control	Straw	SEM[a]	P - value
Number of sows	12	12		
12 hours before labour				
Lying on side (%)	16,11	25,44	3,86	0,121
Lying in ventral position (%)	37,97	36,83	2,67	0,765
Sitting (%)	12,72	7,45	1,31	0,015
Standing (%)	5,36	5,00	0,78	0,746
Stereotype (%)	18,49	7,71	0,96	<.0001
Straw ingestion (%)	-	0,53	0,20	-
During labour				
Lying on side (%)	79,18	88,23	4,66	0,185
Lying in ventral position (%)	10,99	4,05	2,36	0,122
Sitting (%)	4,63	4,03	2,08	0,842
Standing (%)	0,62	0,56	0,36	0,899
Stereotype (%)	1,33	0,68	0,39	0,311
Change of posture , n	38,5	8,10	6,09	0,057
After labour				
Lying on side (%)	63,39	63,14	1,48	0,909
Lying in ventral position (%)	14,50	13,31	1,54	0,592
Sitting (%)	2,84	3,05	0,37	0,696
Standing (%)	2,44	2,48	0,34	0,914
Nursing (%)	11,27	11,87	0,18	0,028
Stereotype (%)	2,27	2,22	0,34	0,920

[a]Standard error of the mean

Statistical analysis

Statistical analyses were performed using the GLIMMIX procedure from the SAS program (SAS 9.4, USA). The effects of the treatments were considered as a fixed effect, whereas the orders of paring of the females were used as a random effect. Pearson correlation coefficients (r) were used to determine the relationships between surface temperature, birth order and nest construction duration.

Results and discussion

There was no effect of straw supply on the surface temperature of the sows before, during and after delivery (Table 2). However, the sows housed in straw treatment crates showed signs of improvement in welfare, with a reduction in the frequency of stereotyped behaviours and a higher frequency of suckling compared to the sows housed in sterile cages.

Table 2. Surface temperature of sows (°C) housed in farrowing crates with or without environmental enrichment in the prepartum period. SEM

	Control	Straw	SEM	P-value
Surface temperature before birth (°C)	36.08	35.79	0.375	0.591
Surface temperature during birth (°C)	36.17	36.79	0.423	0.312
Surface temperature after birth (°C)	36.46	36.46	0.347	0.996

There was a negative correlation between the surface temperature and the birth order of the sows (Table 3). This result indicates that multiparous sows, even after experiencing several deliveries, tend to present increased stress throughout their reproductive life, possibly due to inadequate parturition environment, associating delivery with a negative experience. In a study using piglets, Imfeld-Mueller *et al.* (2011) could conclude that animals were able to anticipate a bad experience after having been exposed to it, presenting a higher frequency of vocalization and signs of fear than animals that never passed by that negative situation.

Table 3. Correlations between surface temperature, the birth order and duration of nest building

	Surface temperature		
	Prepartum	Intrapartum	Postpartum
Birth order	-0.32	-0.22	-0.22
P-value	<0.0001	0.0095	0.0059
Nest building	-0.34	-0.29	-0.35
P-value	0.0005	0.0026	<0.0001

It was observed a lower surface temperature in sows that presented a longer duration of nesting behaviour. Successful nest building feedback causes the sows to stop building them. Females may continue to be motivated to build a nest if they do not have feedback from a complete nest (Damm *et al.*, 2000a). The lack of nesting conclusion response constitutes an acute stress factor, which interferes with maternal hormonal regulation. During birth, physiological changes occur, such as increased plasma concentrations of opioids (Jarvis *et al.*, 1998), however, the concentrations increase at higher than expected

levels if there is acute stress, resulting in inhibition of oxytocin, mediated by opioids (Lawrence *et al.,* 1992). It is possible that the lack of feedback from a completed nest has increased the secretion of opioids and consequently inhibited oxytocin secretion, leading to less calm and behaviours of physiological stress (Pedersen *et al.*, 2003).

The reduction of the superficial temperature of the animals' skin can represent a response to stress, since a peripheral blood flow deviation occurs, directed to the core region and an increase in the deep body temperature, being this phenomenon defined as hyperthermia induced by stress (Nääs *et al.*, 2014; McManus *et al.,* 2016). Variations related to the physiological changes during the stress reaction are evidenced in the auricular pavilion and periocular area, where vasoconstriction occurs (Luzi *et al.,* 2007). Measuring temperature in these highly vascularized areas has a greater relationship with deep body temperature (Soerensen & Pedersen, 2015). In the present study, the superficial temperature obtained from the skin of the body as a whole may not have been a parameter representative of the changes in the deep body temperature, making it difficult to identify a possible reduction of physiological stress with the use of environmental enrichment. In the present study, the superficial temperature obtained may not have been a representative parameter of the changes in the deep body temperature.

Conclusions

The supply of straw as environmental enrichment in the farrowing crates did not affect the body surface temperature of the sows in the prepartum, intrapartum and postpartum periods when compared to the control group. Thus, it was not possible to establish a relationship between environmental enrichment and stress reduction through thermal evaluation. Although sows housed in enriched crates showed signs of improvement in well-being and possibly a reduction in stress, having a stimulus to present the nest building behaviour, reducing the frequency of stereotyped behaviours and have positive effects on the frequency of suckling during lactation. Measuring the temperature of areas such as the eyeball, ears, and snout may be a valid alternative to evaluate if there is a relationship between stress, deep body temperature and environmental enrichment. Use of infrared thermography allows identifying the temperatures of the hottest and coldest surfaces of the pigs and can be a practical tool to analyse facilities and animal welfare.

Acknowledgments

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References

Cabanac, A., & Briese, E. (1992). Handling elevates the colonic temperature of mice. *Physiology & behavior*, 51(1): 95–98.

Damm, B.I., Vestergaard, K.S., Schrøder-Petersen, D.L., Ladewig, J. (2000a). The effects of branches on prepartum nest-building in gilts with access to straw. *Applied Animal Behaviour Science*, 69(2): 113–124.

Hansen, C.F., Hales, J., Weber, P.M., Edwards, S.A., & Moustsen, V.A. (2017). Confinement of sows 24 h before expected farrowing affects the performance of nest building behaviours but not progress of parturition. *Applied Animal Behaviour Science*, 188: 1–8.

Imfeld-Mueller, S., Van Wezemael, L., Stauffacher, M., Gygax, L., & Hillmann, E. (2011). Do pigs distinguish between situations of different emotional valences during anticipation? *Applied animal behaviour science*, 131(3-4): 86–93.

Jarvis, S., Lawrence, A.B., McLean, K.A., Chirnside, J., Deans, L.A., & Calvert, S.K. (1998). The effect of environment on plasma cortisol and β-endorphin in the parturient pig and the involvement of endogenous opioids. *Animal Reproduction Science*, 52(2): 139–151.

Lawrence, A.B., Petherick, J.C., McLean, K., Gilbert, C.L., Chapman, C., & Russell, J.A. (1992). Naloxone

prevents interruption of parturition and increases plasma oxytocin following environmental disturbance in parturient sows. *Physiology & behavior*, 52(5): 917–923.

Lawrence, A.B., Petherick, J.C., Mclean, K.A., Chirnside, J., Vaughan, A., Clutton, E., Terlouw, E.M.C. (1994). The effect of environment on behavior, plasma-cortisol and prolactin in parturient sows. *Applied Animal Behaviour Science*, 39: 313–330.

Luzi, F., Ludwig, N., Gargano, M., Milazzo, M., Carenzi, C., & Verga, M. (2007). Evaluation of skin temperature change as stress indicator in rabbit through infrared thermography. *Italian Journal of Animal Science*, 6(sup1): 769–769.

McManus, C., Tanure, C.B., Peripolli, V., Seixas, L., Fischer, V., Gabbi, A.M., Menegassi, S.R.O., Stumpf, M.T., Kolling, G.J., Dias, E., Costa, J.B.G. (2016). Infrared thermography in animal production: An overview. *Computers and Electronics in Agriculture*, 123: 10–16.

Nääs, I.A., Garcia, R.G., Caldara, F.R. (2014). Infrared thermal image for assessing animal health and welfare. *Journal of Animal Behaviour and Biometeorology*, 2: 66–72.

Pedersen, L.J., Damm, B.I., Marchant-Forde, J.N., & Jensen, K.H. (2003). Effects of feedback from the nest on maternal responsiveness and postural changes in primiparous sows during the first 24 h after farrowing onset. *Applied Animal Behaviour Science*, 83(2): 109–124.

Pedersen, L.J., Malmkvist, J., Andersen, H.M. (2013). Housing of sows during farrowing: a review on pen design, welfare and productivity. In: Aland, A., Banhazi, T. (eds) *Livestock housing: modern management to ensure optimal health and welfare of farm animals*, Wageningen Academic Publishers, Wageningen, pp. 93–112.

Vanheukelom, V., Driessen, B., & Geers, R. (2012). The effects of environmental enrichment on the behaviour of suckling piglets and lactating sows: A review. *Livestock Science*, 143(2-3), 116–131.

Wischner, D., Kemper, N., Krieter, J. (2009). Nest-building behaviour in sows and consequences for pig husbandry. *Livestock Science*, 124(1–3): 1–8.

Soerensen, D.D., Pedersen, L.J. (2015). Infrared skin temperature measurements for monitoring health in pigs: a review. *Acta Veterinaria Scandinavica*, 57(5): 1–11.

Yun, J., Valros, A. (2015). Benefits of prepartum nest-building behaviour on parturition and lactation in sows-a review. *Asian-Australasian Journal of Animal Sciences*, 28(11): 1519–1524.

Heart rate monitoring in pigs using photo pethysmography (PPG) technology

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Abstract

Animal welfare remains a very important issue in the livestock sector but monitoring the overall animal welfare in an objective and continuous way with one sensor, remains a serious challenge. Many methods have been published to monitor abnormal behaviours or components related to animal welfare. Monitoring animal welfare based upon objective physiological measurements, instead of audio-visual scoring of behaviour, would be a step forward. One of the obvious physiological signals related to welfare and stress is heart rate. The objective of this research was to measure heart rate (beat per minutes) on pigs with technology that has come available at large scale for humans and is developed for animals as well. This affordable heart rate monitoring for humans is using the Photo Plethysmography (PPG) technology. We have used PPG sensors on pigs to test whether it allows getting a reliable heart rate signal. We show results of the sensor against a reference measure for heart rate and this for an anesthetized versus a non-anesthetised animal. We have tested three different anatomical body positions (ear, leg and tail) and give results for each body position of the sensor. In summary, we can conclude that the agreement between the cheap PPG-based heart rate technique and a reference sensor goes from 91–97 percentage.

Introduction

Animal welfare remains a very important issue in the livestock sector but monitoring animal welfare in an objective and continuous way remains a serious challenge. However, stress affects many physiological systems that are controlled by the autonomic nervous system, including the cardiovascular system. Monitoring the autonomic nervous system activity in farm animals has recently gained considerable interest worldwide. In farm animals, the vagal component of the autonomic nervous system plays a key role in regulating heart rate (HR) in response to stress (von Holst, 1998; Hopster and Blokhuis, 1994; Kovács *et al.*, 2014). Variables derived from cardiac activity are becoming increasingly important in research of animal health and wellbeing. In general, the variable heart rate (HR) can be used to indicate disease, physiological and psychological stress and to show individual characteristics of animals such as temperament and coping strategies. Electro- and echocardiographic measurements on pigs are also used in research, as pigs are excellent models in human cardiovascular disease due to the similarities in heart characteristics of humans and pigs (von Borell *et al.*, 2007).

Currently, the heart rate of pigs can be monitored in two different ways: with implantable transmitters or with externally mounted non-invasive transmitters. The first method has the disadvantage that the implantation of the transmitters needs to be done under complete anaesthesia. This means that the pigs need a couple of days of recovery after the procedure. Furthermore, complications during the procedure can emerge. For the second method, a portable monitor system that can detect and store electrocardiograms (ECG) for later detection of inter-beats intervals is commonly used. The equipment can consist of coated electrodes mounted around the thorax. The disadvantage is that the signal can be disrupted by movement of the electrode belt either by other pigs or the pig itself (von Borell *et al.*, 2007).

Photoplethysmography (PPG) is a measurement of heart beat rate based on changes in blood flow. Unlike Electrocardiogram (ECG), which measures the heart rate by placing electrodes on the patient's chest, PPG is a low cost, simple, non-invasive optical measurement used in biomedical field to detect blood volume changes in the microvascular bed of tissue through red and infrared lights (Allen, 2007). Regional variations in skin are not the only reasons for the difference in signal quality PPG signal artifacts but also the motion artifacts are one of the main challenges to use the PPG sensors in practice. Motion artifact reduction is the most challenging issue in wearable healthcare sensors including PPG due to body movements. Motion artifacts on signals are considered as the relationship between motion and noise. This includes voluntary and involuntary movements of the interface between the sensor and tissue (Yunjoo Lee *et al.*, 2008). Although sensing components are physically changed to decrease motion artifacts, more analysis is needed to determine which sensor location is the best for monitoring heart rates in pigs.

The present paper is presenting a proof-of-concept study with the aim to determine the optimal location on the pig body, which gives the best PPG signal quality. Additionally, to develop a real-time monitoring algorithm to extract pig's heart rate from PPG signal and to minimize the effect of motion artifacts.

Materials and methods

Experimental setup and measurements

During the course of this study, all measurements were conducted on a female *Göttinger Minipig* (test pig) under both anesthetized and non-anesthetized conditions. The test pig was born on 28.04.2017, had 0.99 m back length (nose to tail), and weight 30.2kg. The experiments were conducted in the Institute for Laboratory Animal Science, Hannover Medical School, Hannover, Germany. The study and all measurements were ethically approved by "Niedersächsisches Landesamt für Verbraucherschutz und Lebensmittelsicherheit" (LAVES) (Germany; 33.12-42502-04-16/2374).

Test on anesthetized pig

During this part of the experiment, the pig was anaesthetized to measure the baseline maximum liver function capacity prior to liver resection (LiMAx measurement). These baseline measurements are always five days before the operation. To anesthetize the pig Zoletil (Tiletamin and Zolazepam, each $mg.kg^{-1}$ i.m.) and Atropine (0.04-0.08 $mg.kg^{-1}$ i.m) were used. The total duration of this part of the experiment was 60min afterward the awakening procedures of the anesthetized pig took place. This time course of 60min was divided into three time slots 20min each. For each time slot, the PPG sensor probe was placed on three different anatomical locations of the test pig, namely ear, upper tail and left back leg (below the knee). These locations of the pig's body were chosen because of their higher cutaneous perfusion and where body fat is low, yet still suitable to place the sensor probe in practice.

Test on non-anesthetized pig

After about one hour of applying the awakening procedure on the test pig, the PPG probe was placed on the left back leg (below the knee Figure 1). Then the test pig was placed to move freely inside a test pin (Figure 1, right photo).

Figure 1. The PPG sensor is placed on the left back leg (below the knee) of the non-anesthetized pig (left photo) and then the animal is placed to move freely in a pin (right photo)

Measurements and sensors

PPG signal

A Shimmer Optical Pulse sensing probe (PPG sensor) together with Shimmer GSR+ module were used to collect PPG signal from the pig. The PPG signal is acquired at sampling rate of 128 Hz.

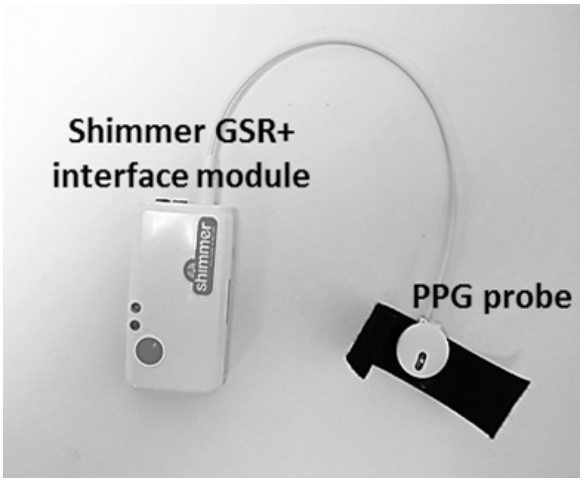

Figure 2. Shimmer Optical Pulse sensing probe (PPG sensor) and data-logger

Gold standard (ECG signal)

As a gold standard for heart rate measurements continuous ECG measurements were preformed. The ECG measurements were performed using a portable ECG recorder, BEAM® ECG 3-channels Loop/Event recorder (IEM GmbH; Stolberg, Germany). It is an on-body portable ECG recorder, with three electrodes to stick on to the skin. The recorded ECG signal is automatically transferred from the BEAM® via Bluetooth to a smartphone and is forwarded from there to a secure database. The BEAM® recorded the ECG data every 0.6 seconds.

Signal processing and heart rate extraction

Figure 3 is showing the main steps of (pre-) processing methodologies to extract the pig's heart rate from the acquired PPG signals. The proposed algorithm consists of four main processing blocks. Each block is explained in detail in the following sections.

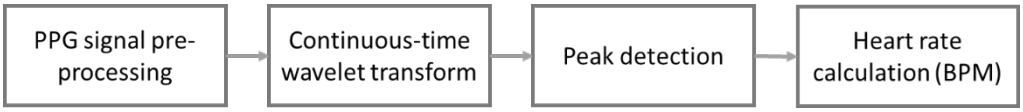

Figure 3. Block diagram showing the main processing steps to extract pig's heart rate from PPG signal

Pre-processing of PPG signals

The PPG signals are often affected by different noise sources such as surrounding lights and motion artifacts (in case of non-anesthetized). Therefore, firstly, the trend is removed using unobserved components (UC) algorithm (Young, 2011) and then, the signals are normalized to zero mean and unit variance (Tang *et al.*, 2016). The normalized signals are filtered using a second order Butterworth high pass filter (cut-off frequency of 0.5 Hz) and first order Butterworth low pass filter (cut-off frequency of 6 Hz). These cut-off frequencies are chosen based on the expected physiological heart rate range.

Wavelet analysis and PPG signal reconstruction

In the biomedical engineering field, Wavelet transform (WT) is often preferred over Fast Fourier Transform (FFT) because most of the physiological signals are non-stationary which makes WT a viable method. Using WT, the signals in the time domain are mapped into the frequency domain in order to preserve both time and frequency information. WT is a spectral estimation technique by breaking a general function into an infinite series of wavelets (Tang *et al.*, 2016).

Continuous Wavelet Transform method

For the continuous wavelet transform (CWT) method of spectral decomposition, the kernel function is a wavelet that adapts to the frequency of interest. In general, a specific wavelet cantered about a given frequency is computed from the mother wavelet by scaling it and shifting. In this manner, the length of the wavelet contains the same number of centre (also called peak) frequency cycles. For a scale parameter, , and position, , the CWT is given by:

$$C(s,b,f(t),\Psi(t)) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{s}} \Psi(t) * \left(\frac{t-b}{s}\right) dt \qquad [1]$$

The Wavelet analysis is performed by convoluting a signal, f(t), with a prototype function called mother wavelet, $\Psi(t)$. As the value of s increases, the wavelet is compressed, its spectrum dilates and the peak frequency shifts to a higher value. Conversely, as the wavelet is scaled such that it dilates, the value of s decreases, its spectrum is compressed and the peak frequency shifts to a lower value. Thus, by varying the scaling factor 's', the wavelet family can represent broadband spectra, wherein the spectrum of each wavelet in the family maintains a constant ratio between its peak frequency and the corresponding bandwidth (Chopra and Marfurt, 2015).

Since the Gaussian function is perfectly local in both time and frequency domains and is indefinitely derivable, a derivative of any order *n* of the Gaussian function may be a Wavelet Transform (WT). For cardiac signal characterization we are interested in a first derivative Gaussian wavelet function (Sahambi *et al.*, 1997). In this paper, the first derivative Gaussian (DOG) Wavelet was used to decouple the cardiogenic (pulsatile) PPG signal using the CWT technique. The processing and analysis of the signals are done using custom script written in MATLAB (The Math Works, Inc.) based on Signal Processing and Wavelet Analyzer toolboxes.

Results and discussions

Wavelet decomposition of the PPG signal

Wavelet transform (WT) allows to decompose the signal into a linear combination of simpler signals in the time-frequency domain, therefore, provides localization of frequency in the time. WT provides multi-resolution analysis of input signal into approximation and details respectively approximation coefficients and detail coefficients.

Figure 4 is showing the pre-processed PPG signal, obtained from the ear of the anesthetized pig, in the time-domain, time-frequency spectrogram and the Welch estimate of its power spectrum density (PSD). The initial analysis of the signal in the frequency domain has shown different components. The PPG signal component within the frequency band 1.66-2.1Hz in the time-frequency spectrogram (Figure 4, [b]), with a centre frequency of 1.81Hz (Figure 4, [c]), is falling within the expected heart rate (HR) range (region of interest) of pigs. In general, the PPG signal acquired from the non-anesthetized (free moving) pig has shown more artefacts (Figure 5) in comparison with all PPG signals acquired from anesthetized pig.

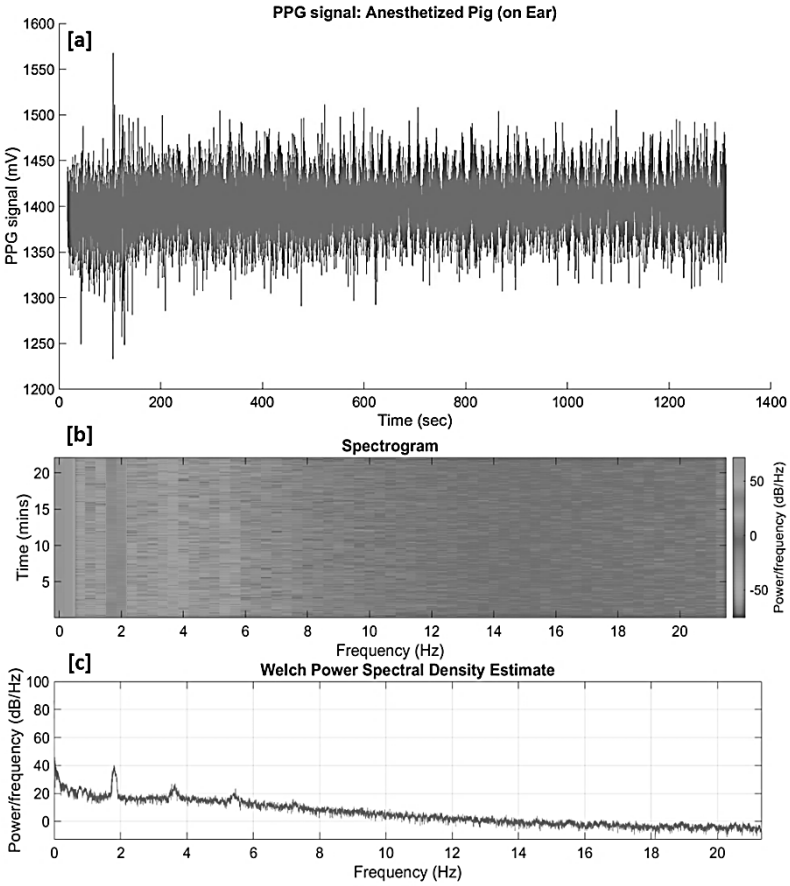

Figure 4. The pre-processed PPG signal acquired from the ear of the anesthetised pig plotted in the time-domain [a], time-frequency spectrogram [b] and the Welch power spectrum density (PSD) estimate [c]

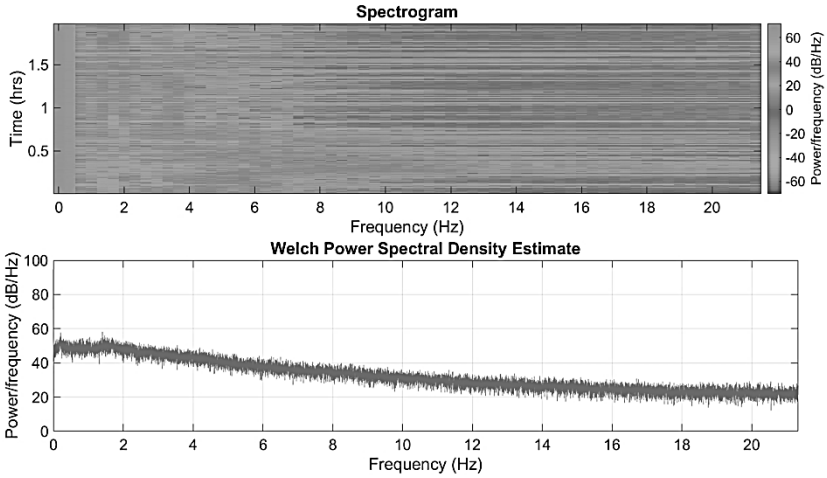

Figure 5. The time-frequency spectrogram (upper graph) and the Welch power spectrum density (PSD) estimate (lower graph) of the PPG signal acquired from the non-anesthetize pig, where the PPG probe is placed on the left leg

To reconstruct the cardiogenic PPG signals, the CWT was implanted using the built-in Matlab function cwtft . The cwtft function returns the continuous wavelet transform (CWT) of the PPG signal using a Fourier transform based algorithm. First derivative Gaussian (DOG) wavelet and scales corresponding to 0.50 – 15Hz were used.

Figure 6 is showing the reconstructed cardiogenic PPG signals from anesthetized pig.

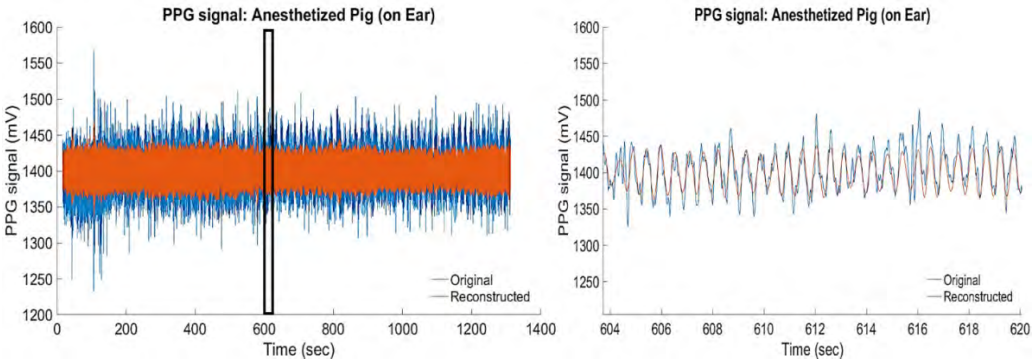

Figure 6. PPG signal (blue) vis wavelet reconstructed signal (red) from pig's ear (left graph), a zoom-in view of the signals(left graph)

Figure 7 is showing the reconstructed cardiogenic signal from the PPG signal obtained from the non-anesthetized pig.

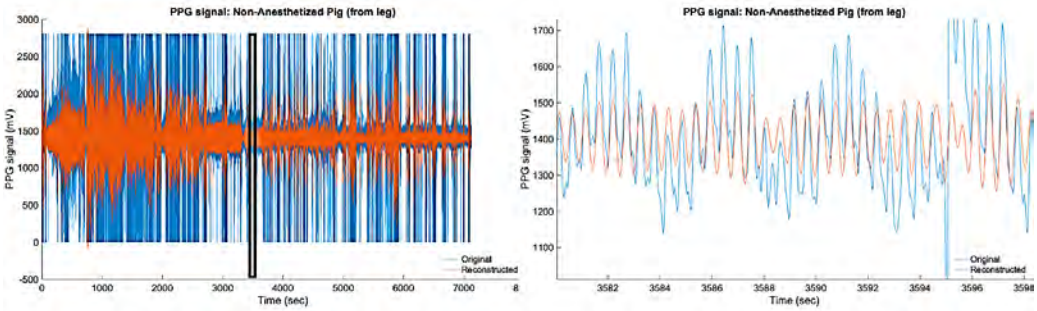

Figure 7. PPG signal (blue) vis wavelet reconstructed signal (red) from non-anesthetized pig's leg

Peak detection and heart rate calculation

The heartbeat could be estimated by measuring the time between the peak intervals in the PPG signal. The proposed algorithm is choosing the tallest peaks of the signal and ignoring all peaks in the predefined minimum separation (time interval) threshold. The algorithm then repeats the procedure of the tallest peak and iterate until it runs out of considerable peaks. Figure is showing an example of the detected peaks from the reconstructed PPG signal obtained from the ear of the anesthetized pig.

The heart rate in bpm was calculated based on the number of detected peaks within a sliding time window or an epoch of one minute with 30 second (50%) overlap Figure 8.

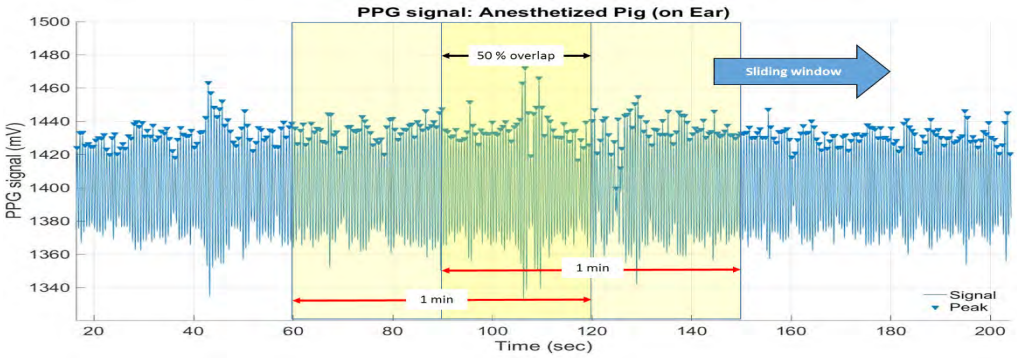

Figure 8. One-minute sliding window with 50% (30 second) overlap to calculate the heart rate (bpm) based on the number of detected peaks per time window

The estimated heart rate from the PPG signal are compared with the ground-truth heart rate (reference), which is calculated from the gold standard ECG signal. The performance of the developed algorithm is then evaluated in terms of the quality of the pulse rate estimation, which is assessed using the Absolute Maximum Error (AME), Mean Absolute Error (MAR) and the Root Mean Square Error (RMSE) that are given as follows:

$$AME = |HR_{PPG}(k) - HR_{ECG}(k)|,$$

$$MAE = \frac{1}{N}\sum_{k=1}^{N}|HR_{PPG}(k) - HR_{ECG}(k)|.$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(HR_{PPG}(k) - HR_{ECG}(k)\right)^2}$$

where N is the total number of data points, $HR_{PPG}(k)$ and $HR_{ECG}(k)$ are the estimated heart rate from the PPG signal and that calculated from the ECG, respectively, at time instant k. RMSE is more sensitive to large estimation errors than MAE, so small number of large errors results in high RMSE and low MAE. Table 1 is showing the MAE and RMSE values for the estimated pulse rate (bpm) from the PPG signal acquired from different body position of the test pig using the developed algorithm.

The quality of the estimated pulse rate form the PPG signal was also assessed using the signal-to-noise ratio (SNR). The SNR in dB is defined as

$$SNR = \frac{\sum_{k=1}^{N} x(k)}{(\sum_{k=1}^{N} [x(k) - f(k)]^2}$$

where x is the original PPG signal and f is the reconstructed cardiogenic signal. SNR compares the level of a desired signal (pulsatile cardiogenic signal) to the level of background noise. Table 1 is showing the calculated SNR values of the PPG signals obtained from different pig body positions (ear, leg and tail) under both anesthetized and non-anesthetized conditions.

Table 1. The Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and SNR of the estimated pulse rate (bpm) in comparison to the reference pulse rate calculated from the ECG signals obtained from the test pig under both anesthetized and non-anesthetized conditions

Source of the PPG signal	ear†	leg†	tail†	leg‡
MAE	2.66	1.75	1.08	3.12
RMSE	3.50	2.27	1.36	3.93
SNR (dB)	19.82	17.53	16.30	10.35

† Anesthetized pig, ‡ Non-anesthetized pig

Figure 9 is showing plots of the estimated pulse rate (bpm) from the PPG signal in relation to the reference pulse rate (bpm) measured from ear, leg and tail of the anesthetized pig.

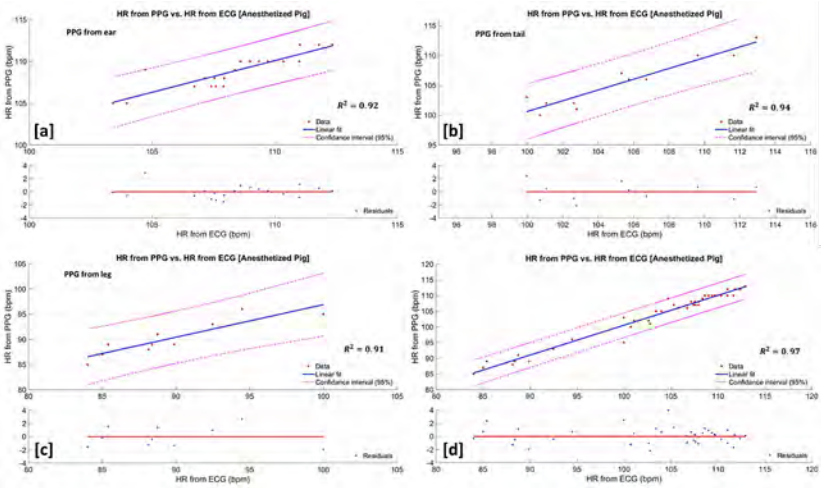

Figure 9. Estimated heart rate from PPG signal vs. heart rate from the gold standard (ECG) measured from the anesthetized pig's ear (a), the tail (b) and the leg (c). The overall heart rate calculated from the PPG vs. that calculated from the gold standard ECG (d)

Conclusions

In this paper, a PPG sensor system was used to measure heart rate (HR) from a *Göttinger Minipig* under anesthetized and free-moving (non-anesthetized) conditions. The PPG probe was placed on three different anatomical body positions, namely ear, leg and tail. The pulsatile cardiogenic signals were reconstructed using continuous wavelet transform (CWT). The peaks of the pulsatile cardiogenic signal were detected and pulse rate (bpm) were estimated from the PPG signals using the developed algorithm. The estimated HR from free-moving pig (PPG probe placed on the leg) have shown the highest RMSE and MAE (3.93 and 3.12, respectively) and lowest SNR (10.35 dB). The resulted have shown that PPG signals obtained from the ear contained the highest SNR (19.82 dB). In general, it was possible to reconstruct the pulsatile cardiogenic signals and estimate the pulse rate of the pigs from PPG signals obtained from the three different body positions with accuracy level between 91-97%.

References

Allen, J. (2007), "Photoplethysmography and its application in clinical physiological measurement", *Physiological Measurement*, 28(3): R1–R39.

von Borell, E., Langbein, J., Després, G., Hansen, S., Leterrier, C., Marchant-Forde, J., Marchant-Forde, R., *et al.* (2007), "Heart rate variability as a measure of autonomic regulation of cardiac activity for assessing stress and welfare in farm animals — A review", *Physiology & Behavior*, 92(3): 293–316.

Chopra, S. and Marfurt, K.J. (2015), "Choice of mother wavelets in CWT spectral decomposition", *SEG Technical Program Expanded Abstracts 2015*, Society of Exploration Geophysicists, pp. 2957–2961.

von Holst, D. (1998), "The Concept of Stress and Its Relevance for Animal Behavior", *Advances in the Study of Behavior*, *Academic Press,* 27: 1–131.

Hopster, H. and Blokhuis, H.J. (1994), "Validation of a heart-rate monitor for measuring a stress response in dairy cows", *Canadian Journal of Animal Science*, NRC Research Press Ottawa, Canada, 74(3): 465–474.

Kovács, L., Jurkovich, V., Bakony, M., Szenci, O., Póti, P. and Tőzsér, J. (2014), "Welfare implication of measuring heart rate and heart rate variability in dairy cattle: literature review and conclusions for future research", *Animal*, 8(02): 316–330.

Sahambi, J.S., Tandon, S.N. and Bhatt, R.K.P. (1997), "Using wavelet transforms for ECG characterization. An on-line digital signal processing system", *IEEE Engineering in Medicine and Biology Magazine*, 16(1): 77–83.

Tang, S.K.D., Goh, Y.Y.S., Wong, M.L.D. and Lew, Y.L.E. (2016), "PPG signal reconstruction using a combination of discrete wavelet transform and empirical mode decomposition", *2016 6th International Conference on Intelligent and Advanced Systems (ICIAS)*, IEEE, pp. 1–4.

Young, P.C. (2011), *Recursive Estimation and Time-Series Analysis: An Introduction for the Student and Practitioner*, Springer.

Yunjoo Lee, Hyonyoung Han and Jung Kim. (2008), "Influence of motion artifacts on photoplethysmographic signals for measuring pulse rates", *2008 International Conference on Control, Automation and Systems*, IEEE, pp. 962–965.

Environmental control system for pig farm based on mobile coordinator routing algorithm

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Abstract

In order to improve monitoring and management efficiency of large pig farms, an environmental control system for pig farm based on mobile coordinator routing algorithm was designed. This system consisted of the remote control terminal, the field controller with ARM-LINUX and the wireless networks composed of various devices and sensors. In order to realise the systematic management of all kinds of equipment in a pig farm, the environmental parameter sensors (such as temperature, humidity), control equipment (such as negative pressure fan, hot blast furnace, water valves) and cameras were used to constitute wireless networks by ZigBee technology. In order to prolong the nodes lifetime of the wireless networks, a clustering routing algorithm with a mobile coordinator was proposed. The coordinator node and the field controller were installed on the patrol car with battery to overcome the energy shortage. The operation cycle of wireless networks in the algorithm is divided into a clustering phase and data transmission phase. In the clustering phase, cluster heads (CHs) were selected by an optimal threshold in energy, and the wireless networks were constructed nearby. During the data transmission phase, the coordinator node moved with the movement of the patrol car, and the coordinator node communicated with the nearby cluster head nodes. The transmission distance between the coordinator and cluster head node was optimized and shortened based on LEACH algorithm. The proposed algorithm reduced the energy consumption rate of cluster heads, avoided the premature generation of death nodes in the networks, and improved the lifetime and transmission efficiency of the networks.

Keywords: environmental control system, wireless network, mobile coordinator; pig, routing algorithm

I. Introduction

At present, the pig industry in China is developing towards the trend of large-scale, and the information management of pig farm is becoming more and more important. The environment of traditional pig farms is usually managed by manual mode. The mode not only takes up a lot of manpower but also has obvious shortcomings in real-time, operability and other aspects. The field equipment generally connects with a processor by cable. It will cause pig farm wiring to be complex and more difficult to maintain. So it is urgent to design an intelligent control system based on a wireless sensor network to solve these problems.

The energy of wireless sensor network (WSN) node is limited, and it is an important factor in restricting the development of a wireless sensor network.The energy consumption of nodes should therefore be reduced as much as possible. At present, in terms of network energy optimization algorithm, a lot of research has been done at home and abroad. For example, in the light of the problem of energy consumption caused by uniform clustering, a non-uniform clustering algorithm based on energy balance is proposed by Wang Yingying. It adds a node density function in the algorithm, it can increase the probability that the nodes in the high density area are selected as the cluster heads (CHs), and reduce the probability of the nodes in the low density area becoming the CHs. It makes the

CHs relatively evenly distributed in the network according to the distribution of nodes. Kuilan Pratyay *et al.* proposed a particle swarm optimisation algorithm based on energy efficient clustering. This algorithm is divided into two parts, the routing algorithm and the clustering algorithm. The routing algorithm is developed from the efficient particle coding scheme and the multi-objective fitness function. The clustering algorithm is proposed by considering the load balance and the residual energy of the nodes. Saeid Mottaghi *et al.* proposed an algorithm called Optimizing LEACH clustering algorithm with mobile sink and rendezvous nodes. In the algorithm, the rendezvous nodes (RNs) acts as store points for the mobile sink (MS). By the movement of the sink, the communication distance between nodes is reduced, and the total energy consumption of the network is reduced. Banerjee Ritwik *et al.* proposed an optimal routing algorithm which contains a mobile sink. In the algorithm, CHs uses multi-hop mode to communicate with the sink, and the sink moved along the predetermined trajectory. It solves the problem of the load balancing problem of each cluster and the energy hole caused by the fixed sink. Inspired by those algorithms, we proposed an energy optimised routing algorithm with a mobile sink.

In this paper, an environmental control system for a pig farm was designed based on embedded technology and wireless sensor networks technology. Based on the system, the paper focuses on the routing algorithm in the wireless sensor network. A clustering routing algorithm with mobile sink based on LEACH (Low-Energy Adaptive Clustering Hierarchy) is proposed. LEACH algorithm adopts the fixed sink, and the CHs may communicate with the sink in a long distance, so the CHs will consume a large amount of energy. To address this deficiency, through optimising the transmission distance between CHs and sink, we introduce a mobile sink to form a new algorithm. This algorithm not only solves the problem of excessive energy consumption of CHs but also solves the problem of uneven energy consumption of the network. This algorithm guarantees the real-time monitoring of the environment of pig farm for a long time.

Materials and methods

A. Overall design of the system

According to the design requirements, we use wireless sensor network technology, embedded technology, and others to design an environment control system for a pig farm based on the mobile sink routing algorithm. The system is mainly divided into three parts: information acquisition subsystem, field control subsystem and remote control terminal. The overall block diagram of the system is shown in Figure 1.

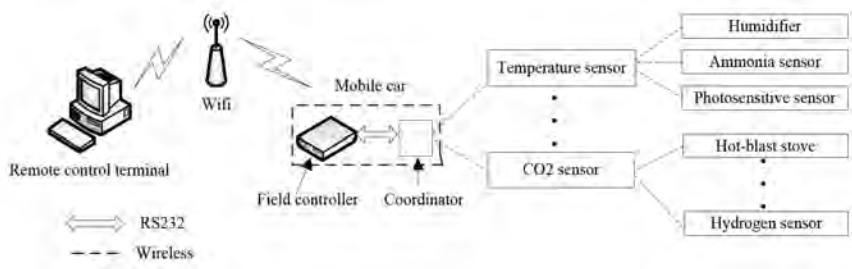

Figure 1. The overall block diagram of the system

The information collection subsystem is composed of Zigbee wireless sensor nodes which are distributed in the pig farm, and the Zigbee node is installed with temperature, humidity, ammonia, hydrogen sulfide, carbon dioxide and other sensors, as well as negative pressure fan, hot air furnace and other on-site equipment. Various sensors can be used

to collect environmental information. Each node transmits the data to the coordinator through Zigbee wireless technology. The coordinator then transmits the received data to the field control subsystem through RS232 serial. In this control system, the coordinator and the field controller are installed on a tracking robot car to achieve the purpose of mobile sink in wireless sensor network. At the same time, the car is also equipped with audio sensors, cameras and a variety of environmental sensors, and these components are directly connected with the field controller. Through the mobile car, on the one hand, the environmental monitoring of a large area of the pig farm can be realised, on the other hand it can capture the activity of pigs. For example, the audio sensor can detect the pig cough, the camera can real-time monitor some key areas (such as the place of sow farrowing).

The field control subsystem analyses the received data and feedback of the corresponding control information to the terminal equipment node in Zigbee network, and the node control of the operation of the device by controlling the relay. We need to transplant a database on the tiny6410 platform to achieve the storage of data. Tiny6410 connects to the internet by WiFi, and it should build an embedded web server to provide the conditions for the remote monitoring.

The remote control terminal is the monitoring and management platform of the pig farm. The system uses the B/S management model, users can view the piggery environmental information and control the corresponding field equipment to make pigs live in the best growing environment by the terminal.

B. Wireless sensor network architecture

The Zigbee wireless network in pig farm using cluster topology along with various sensors, negative pressure fan, hot air furnace and other field equipment which are installed on the network nodes in each pigpen, according to the need to install a plurality of temperature and humidity sensor, audio sensor (for collect pig cough, noise and other audio information), camera and ammonia, hydrogen sulfide, carbon dioxide and other harmful gas sensors. We also install an automatic feeding trough and drinking water equipment (to extract the amount of food, drinking water information) along with a vacuum blower, hot stove, mosquito repellent lamp, cooling plate and other equipment to control the piggery environment. The above pig control equipment and various sensors formed the WSN of pigpen, the wireless sensor network model of the system is shown in Figure 2.

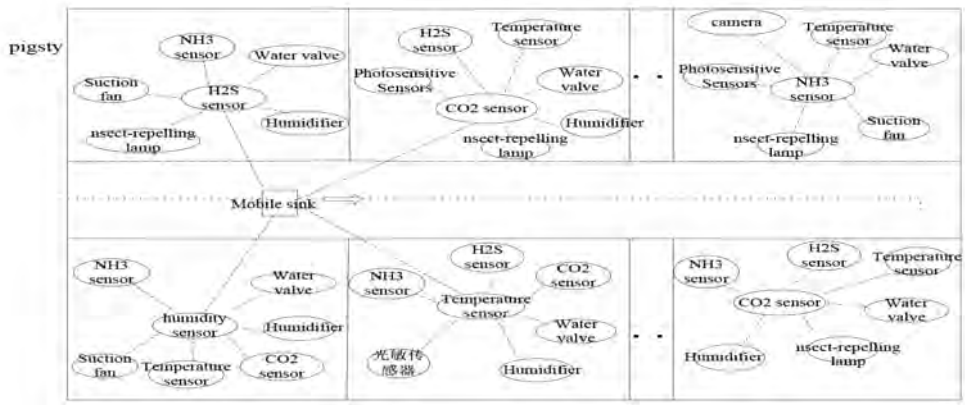

Figure 2. The wireless sensor network model of the system

C. The routing algorithm based on mobile sink

In this paper, a clustering routing algorithm with a mobile sink is proposed, which is called CLMS (Clustering Low-energy-algorithm based on Mobile Sink). In the algorithm, the mobile sink moves along a predetermined trajectory. The member nodes collect environmental data, and transmit the data to the CHs. The CHs wait for the sink to approach, and then send the data to the mobile sink. The algorithm was split into several rounds that are similar to LEACH, each round start with a setup-phase and continues with a steady-state phase. The setup-phase consists of two stages. The first stage is CHs selection. The next stage is cluster setup, where the clusters are developed. The second phase is the steady-state phase in which node data is transmitted to the MS; this phase contains a single stage called data transmission.

The energy model of the algorithm: the present study used a basic energy model to calculate energy consumption during transmission or receipt of data. In this model, energy consumed to transmit *l* bits of message to a location *d* meters in distance of:

$$E_{Tx}(l, d) = \begin{cases} l \times E_{Tx} + l \times d^2, & d < d_0 \\ l \times E_{Tx} + l \times d^4, & d \geq d_0 \end{cases} \tag{1}$$

where

$$d_0 = \sqrt{\frac{E_{fs}}{E_{amp}}} \tag{2}$$

E_{Tx} is the energy consumed by the radio electronic circuit for l bit transmission, E_{fs} is the energy consumed by the power amplifier on the free space model, and E_{amp} is the energy consumed by the power amplifier in the multi-path model. The total energy consumed to transmit and receive data is:

$$E_{total} = E_{TX}(1, d) + E_{Rx}(1) \tag{3}$$

1) Cluster heads (CHs) selection

A node decides to become a CH based on the percentage of existing CHs, the number of times that the node has previously been selected as a CH and its level of energy. If the energy level of the node is more than or equal to average energy of all nodes, that node can potentially participate in CH selection. If the node does not have the required conditions to participate in CH selection, it will cause a delay of 1/p in round. The node then generates a random number between 0–1. If this number is less than threshold T(n), the node will become a CH in this round and the CH label will attach to it. The number of cluster heads should be appropriate, and the optimal proportion of CHs is:

$$p = \sqrt{\frac{N}{2\pi}} \frac{2}{0.765} \tag{4}$$

Where, N is the number of nodes. It can be seen that the optimal proportion of CHs is only related to the number of nodes in the network. The threshold is:

$$T(n) = \begin{cases} \dfrac{p}{1 - p \times (r \bmod \frac{1}{p})} \times \dfrac{E'}{E_0} \times \dfrac{r'}{r}, n \in G \\ 0, \qquad others \end{cases} \tag{5}$$

Where, p is the CHs percentage, r denotes the current round and G is the set of nodes that have not been CHs in the last 1/p rounds. E_0 is the Initial energy and E' is the current energy. At this threshold, each node will be CH within 1/p rounds.

2) Cluster selecting

After the CHs are selected, each CH broadcasts an advertisement message to normal nodes (NNs). Each NN decides to which cluster it belongs, and the decision is based on the distance between NNs and CHs. The signal strength of the advertisement message will determine which CH is closest to an NN. The nearest CH produces the largest signal.

When the nodes are organised into clusters and have received all node information messages, each CH creates a schedule based on TDMA protocol. The CH broadcasts a message to inform each node when it will transmit data. Determining the schedule for the nodes allows the radios to be turned off during the CH allocated time slot, which decreases energy consumption in the nodes.

Results and discussion

A. Simulation experiment of the routing algorithm

The simulation model consists of 50 wireless sensor nodes which distributed in the size of 100 × 8 meters with two grid area. The wireless signal transmission range is 20 meters, after the network established, the traffic generator starts to work. It will send a data packet of 50 bytes each time and update every 10 seconds. The initial energy of the node is 10.0J, and it is regarded as the death node when the energy is less than 2.0J.

1) Comparison of energy consumption of each node

Figure 3 shows the energy consumption rate of each node in CLMS and LEACH for a period of time. The higher consumption rates among them are CHs. CLMS contains a mobile sink, which is moving in the network. Only when the sink is close to the CHs, the CHs will communicate with the sink. Compared to LEACH which has a fixed sink, CLMS greatly reduces the communication distance, thus reducing the energy consumption of CHs. As can be seen from figure, 3rd, 7rd, 16rd and other nodes are CHs, and consume more energy than NNs. The energy consumption of NNs in the two algorithms is not very different, but the energy consumption of CHs in CLMS is significantly lower than that of LEACH. The average energy consumption of nodes under CLMS is 0.014371J/sec, and the average energy consumption rate of LEACH is 0.019172J/sec. It is proved that the algorithm is optimised for the energy consumption of nodes.

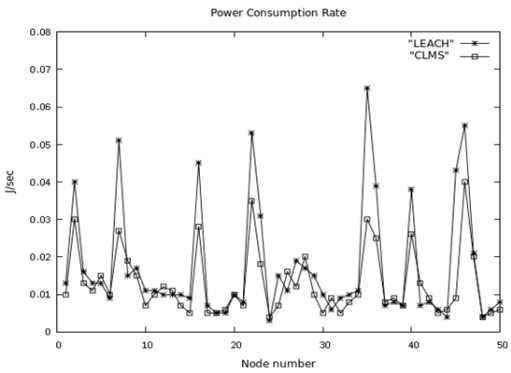

Figure 3. The energy consumption rate

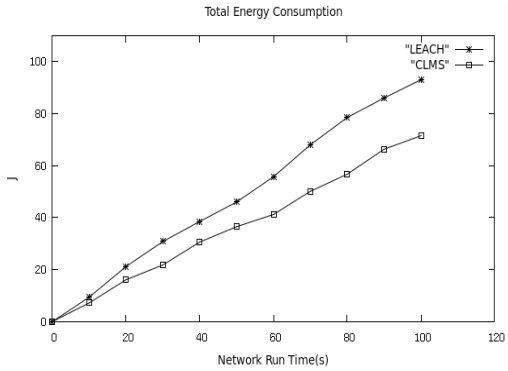

Figure 4. The overall energy consumption

2) Comparison of the total energy consumption

Figure 4 is the comparison of the overall energy consumption of the network over a period of time. Because the CHs can store data and there is MS in CLMS, the average communication distance of the network is shorter, so the average energy consumption of the network nodes is reduced, and the total energy consumption of the network is reduced to a certain extent. From the graph, we can find that CLMS has better performance than LEACH in terms of energy consumption. For example, when the network runs to 80 seconds, CLMS consumes a total of 58.31J, while LEACH consumes 75.83J. With the time runs, the gap between the two gets bigger and bigger. Therefore, the algorithm that was proposed in this paper can reduce the energy consumption of the network to a certain extent.

3) Comparison of the number of survival nodes

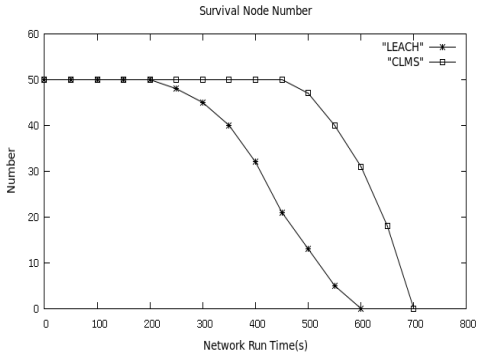

Figure 5. Comparison of survival nodes

Figure 6. Monitoring web page

The CHs need to transmit more data in WSN and will consume more energy, and die sooner. CLMS shortens the distance of data transmission of CHs and greatly reduces the energy consumption of CHs. It can delay the death of the CHs and balance the energy consumption of the nodes. As can be seen from Figure 5, the death nodes in LEACH are concentrated between 250th seconds to 600th seconds, and the death nodes in CLMS are concentrated between 450th seconds to 700th seconds. The first and the last death node in CLMS are later. It can be proven that CLMS has a good effect on the life of the nodes, and the energy consumption of the network nodes is more balanced.

B. Test of environmental monitoring system

The sink in CLMS can move so the coordinator and the tiny6410 should be mounted on a tracking robot car, and they can then move in the pig farm by car. The ZigBee wireless network is up and running and the sensor nodes start working. Sensor nodes send the collected data to tiny6410 and users can see the environmental information on the remote browser through the internet, including temperature, humidity, CO_2 concentration, hydrogen concentration, etc. It can control the on-site equipment automatically in the pig farm. The results verify the feasibility of the monitoring system and the remote monitoring web page as shown in Figure 6.

Summary

This paper proposed an environment control system for a pig farm based on mobile sink routing algorithm. We focus on the routing algorithm of the wireless sensor networks. By movement of the sink, the transmission distance between the sink and the CH is shortened. It not only reduces the energy consumption of the CH, but it also balances the energy consumption of the network. The results of the simulation show that the algorithm

reduces the energy consumption of the CHs, extends the lifetime of the sensor nodes and the entire wireless sensor network, so that the environment control system can work for a longer time. The control system can realise the monitoring and management of the pig farm effectively.

References

Ali, Abdul Wahid. "Parmanand.Energy efficieny in routing protocol and data collection approaches for WSN: A survey," International Conference on Communication and Automation ICCCA2015, p540–545.

Liang W, Luo J, Xu, X. "Prolonging network lifetime via a controlled mobile sink in wireless sensor networks," In:Global telecommunications conference, 2010, December: 1–6.

Pratyay Kuila, Prasanta, K. "Energy efficient clustering and routing algorithms for wireless sensor networks: Particle swarm optimization approach," Engineering Applications of Artificial Intelligence, 2014, 33(2): 127–140.

Ritwik Banerjee, Chandan Kr. "Energy Efficient Routing and Bypassing Energy-Hole through Mobile Sink in WSN," 2014 International Conference on Computer Communication and Informatics (ICCCI-2014), 2014, 1(3): 03–05.

Saeid Mottaghi, Mohammad Reza Zahabidi. "Optimizing LEACH clustering algorithm with mobile sink and rendezvous Nodes," *International Journal of Electronics and Communications,* 2015, 69(21): 507–514.

Santhosh Kumar, Vinu Paul MV. "Mobility metric based LEACH-Mobile protocol," International Conference on Advanced Computing and Communications, 2008, 16(13): 248–253.

Weixing Zhu, Chenyun Dai, Peng Huang. "Environmental monitoring and control system for pig farms based on Internet of things," *Journal of Agricultural Engineering,* 2012, 28(11): 177–182.

WU Xiaoping, LIN Hong, LI Gang. "An Improved Routing Algorithm Based On LEACH Protocol," IEEE Computer Society. 2010, 9(8): 259–262.

Yingying Wang, Xianling Lu. "Energy efficient routing algorithm for Wireless Sensor Networks," *Journal of Jiangnan University,* 2014, 6(8): 12–17.

Yue Haidi, Bohnenkamp Henrik. "Analysing and improving energy efficiency of distributed slotted Aloha," Smart Spaces and Next Generation Wired/Wireless Networking - 11th International Conference, 2011, p197–208.

Zhanyang Xu, Yue Yin."Energy efficient clustering algorithm for Wireless Sensor Networks," *Computer Engineering and Design,* 2014, 5(8): 35–39.

Modelling precision grass measurements for a web-based decision platform to aid grassland management

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Abstract

GrassQ is an ICT-Agri Era-Net funded EU project aimed at developing and combining precision grass measurement systems into a web based decision platform to aid precision grassland management. Novel and conventional systems of measuring grass yield and quality were developed and refined in Ireland, Denmark, Finland and Switzerland. The measurement parameters were compressed sward height (CSH, mm), herbage mass (HM, kg DM ha^{-1}), dry matter (DM, g kg^{-1}) and crude protein (CP, g kg^{-1}). A protocol was developed for the rising plate meter (RPM), for grass measurement optimisation. Initial evaluation indicates mean CSH can be predicted to ± 5% SE using 35 samples ha^{-1}. Region, sward and seasonal specific HM prediction models are being developed to further increase the accuracies of the RPM ($R^2 > 0.7$). A preliminary lab based near infrared spectroscopy (NIRS) fresh grass quality calibration was developed with positive results ($R^2 > 0.94$ and $R^2 > 0.90$, for DM and CP). An alternative technology of multispectral sensing was carried out using a range of airborne methods including an Unmanned Aircraft System (or Drone) and data from the EU Sentinel 2 satellite were also acquired. Grass biomass was estimated at a reasonable level by processing Sentinel-2 and Drone multispectral data using partial least square regression (PLSR) and at a moderate level using stepwise multilinear regression (MLR). In Finland, estimations for grass silage swards using Random Forest (RF) analysis with 3D features and based on point cloud and image spectral features, indicated R^2 values similar to those obtained in Ireland. The prototype GrassQ web platform using data from the aforementioned models, is now operational and currently under evaluation.

Keywords: grass measurement, herbage mass.

Introduction

Grazed grass is the primary feed source for the Irish dairy and beef industries, due to the suitability of the temperate Irish climate for growing grass. This has resulted in Irish dairy production being amongst the lowest cost production systems in the world (Dillon *et al.,* 2008). In contrast to this, global grass based systems are in decline, with a 30% decrease in Europe alone (Huyghe *et al.,* 2014), as a result of the increased output and feeding efficiencies that can be achieved from feed lot based systems. Shalloo *et al.* (2005) identified how grazing systems have the potential to achieve higher outputs in a financially sustainable manner, but are hindered by the reduced control of herbage availability and quality. Available herbage is defined as herbage mass (HM) (kg DM ha^{-1}), which is the dry weight yield of grass per hectare. Optimal grass allocation to the herd is integral to precision grassland management. Excess allocation leads to wastage and quality derogation and insufficient allocation leads to a decline in animal performance and pasture damage. Accurate HM estimation is essential in optimising grass utilisation and allocation, thereby increasing profit margins (French *et al.,* 2015). A number of different methodologies exist by which grass quantity and quality parameters are estimated. These methodologies need

to generate accurate measures, be robust, easy and quick to conduct and compatible with new technologies. This study examines two different approaches to grass measurement using the very different techniques, which may be described as ground-based and remote sensing techniques.

Traditional ground based techniques include a rising plate meter (RPM) which is an established method of predicting HM by measuring compressed sward height (CSH) and is considered to be a rapid, non-destructive and effective means of estimating available herbage (O'Donovan *et al.*, 2002; Sanderson *et al.*, 2001). More recently, the Grasshopper (TrueNorth Technologies Ltd.) an automated CSH measurement tool, has been developed based on the conventional RPM concept. There is scope for increasing the precision of this system. It is reasonable to assume that increasing sampling area and resolution will, in turn, increase precision, but this further increases sampling time and cost. Grassland management currently makes up 13% of annual labour allocation on Irish dairy farms (Deming *et al.*, in press). The spatial and temporal variation in HM can be significant within grassland swards (Bailey *et al.,* 2000) and this can also have a direct effect on pasture allocation and utilisation. Therefore, the first objective of the study was to develop a grass CSH measurement protocol that would optimise accuracy while minimising measurement time. The second objective was to improve the overall precision of the RPM with regard to modelling the HM estimation, so that it can be incorporated into a precision grass measurement system to optimise decision management platforms. However, it is also necessary to have accurate estimates of the chemical constituents and quality parameters of the grass. While Near Infrared Spectroscopy (NIRS) is a well-established method of determining these parameters in dried and milled forages, limited research has been conducted on the application of NIRS to predict un-dried fresh grass quality. Thus, a further aim of this study was to investigate the potential of NIRS to predict quality parameters, dry matter (DM, g kg^{-1}) and crude protein (CP, g kg^{-1}DM), in fresh un-dried grass. Finally, an alternative technology of multispectral sensing was carried out using a range of airborne methods including an Unmanned Aircraft System (or Drone) and data from the EU Sentinel 2 satellite were also acquired. Spectral models were developed from all data sets to enable grass quality and quantity prediction. Knowledge of all of these parameters would enable more precise allocation of quality herbage to grazing livestock.

Materials and methods

Sampling and measurements were conducted at the Teagasc Animal & Grassland Research Innovation Centre at Moorepark, Fermoy, Co. Cork, Ireland. Perennial ryegrass cultivar trial plots (5*1.2 m) were selected for analysis. The plots (N = 64) were arranged in a randomised complete block design, with a 16*4 factorial arrangement. The trial consisted of four treatment groups in accordance to the rate of nitrogen fertilizer applied, with each group consisting of four replicates. Treatment groups had 0 kg ha^{-1}, 119 kg ha^{-1}, 244 kg ha^{-1}, and 480 kg ha^{-1} of nitrogen applied respectively, per plot on a weekly basis.

A blanket sampling scheme was devised to best estimate the 'True mean' CSH within each plot. To minimise the effects of bias and double sampling, the authors designed a custom built sampling grid reference rig (*Fermoy Engineering Services*). The rig design enabled the maximum practical amount of samples (N = 39) to be taken within each individual plot without double sampling and to within a point tolerance of ±10 mm. The CSH samples were taken weekly on each of the 16 plots. Measurements were taken using the Grasshopper RPM. Directly after the CSH measurements, plot cuts were taken and weighed to determine herbage yield. Sub samples were taken for NIRS analysis in the lab and for further reference analyses for DM and CP. The CSH measurements (n = 16,692) and plot cuts (n = 432) were taken over 27 dates between March - October 2017**.** Recorded data were automatically

uploaded and saved onto the user's Smartphone (Apple iPhone 5S, IOS, Apple Inc.), using the Grasshopper Smartphone application (Grasshopper 1.2). Data recorded in the field was later downloaded onto a PC for processing and analysis. To investigate optimum sampling rates, all data gathered from each of the 16 plots harvested per sampling date were pooled to simulate a small paddock (area = 96 m^2), with prominent sward heterogeneity, resulting from the variation of applied nitrogen between the plot groups. Retrospective sample reduction analysis was carried out using Microsoft Excel (2010). A randomization function was employed to simulate reducing sampling rates incrementally in a random stratified manner. Random stratified sampling was selected as a suitable sampling strategy, as it is considered an effective means of capturing information on variances within a sample area in an unbiased and spatially balanced manner (Webster & Lark, 2012) and has been utilised by similar studies in this area (Hutchinson *et al.*, 2016; Jordan *et al.*, 2003).

All CSH data gathered from the grass plot cuts over the grazing seasons (to identify the seasonal effect), was cross referenced with wet chemistry analysis and metrological data, and used in the formulation of conceptual HM prediction models. Prediction modelling is on-going and includes basic linear, logarithmic and multi-linear models to predict HM using all data gathered and also seasonal regression models relating CSH to HM. Those conceptual outcomes are being scaled up and trialled on grazed paddocks currently and it is planned to test the refined models on different grass species in different regions throughout Ireland, Switzerland and Denmark in the coming months.

Perennial ryegrass samples (n = 1,366) collected from plots and grazed paddocks on an on-going basis, over two grazing seasons (as described above) were scanned using a FOSS 6500 spectrometer at 2 nm intervals in the range of 1,100 nm – 2,500 nm and absorption was recorded as log 1/Reflectance. Reference analyses were carried out (as above) for DM and CP and combined with the spectral data. A validation set (n = 205) was selected randomly and maintained separate from the original dataset. The remaining data were used to derive multiple prediction calibrations, by means of partial least squares regression using WinISI chemometric modelling software.

Two Remote Sensing technologies were assessed in GrassQ at the Irish test-site; Spaceborne Sentinel-2 and the more compact Sequoia Multispectral sensor which was attached to an Unmanned Aircraft System (or Drone). Data were collected at the Moorepark grass test-site (Fermoy, Co Cork, Ireland) over the course of 18 months – at varying intervals to match dates when grass-sample cutting and subsequent laboratory analysis was carried out. Overall, five sets of ground based samples were used to develop prediction models of grass biomass using the multispectral imagery (Sentinel-2, Drone). Prior to spectral modelling, geomatic and radiometric corrections were performed on spectral data sets. All pre-processing and statistical analyses for partial least square regression (PLSR) were performed using Unscambler software (version X10.4.1; CAMO software, Woodbridge, NJ, USA). MLR was carried out using SPSS v. 21 (SPSS Inc.). Drone multispectral datasets were trasformed to surface reflectance images whilst Sentinel-2 images were downloaded as 'Level 2A Products' which had been atmospherically corrected. Twenty spectral indices which had been reported as practical indices for assessing vegetation quality parameters in published literature were selected for spectral prediction of measured grass biomass. Calculated indices were: Normalized Difference Vegetation Index (NDVI), Modified Chlorophyll Absorption Ratio (MCAR), Modified Non-Linear Index (MNLI), Green Normalized Difference Vegetation Index (GNDVI), Soil Adjusted Vegetation Index (SAVI), Leaf Chlorophyll Index (LCI), Modified Triangle Vegetation Index (MTVI) , MERIS Terrestrial Chlorophyll Index (MTCI), Nitrogen Reflectance index (NRI), Red-edge Chlorophyll Index (CI-RedEdge), Green Chlorophyll Index (CI-Green), Non Linear Index (NLI). Partial least

square regression is commonly used for developing spectral prediction in agricultural land uses (Cho *et al.*, 2007; Li *et al.*, 2014). Multilinear regression (MLR) has been also reported as reliable a method for spectral based estimation of plant attributes (Park *et al.*, 1997; Cheng *et al.*, 2015).

Results and discussion

Recorded CSH ranged from 134 mm in mid-summer to 53 mm in late autumn; with an annual mean of 88 mm. Mean annual CV of CSH was 16% and ranged from 14% in autumn to 19% in early spring. The decaying exponential relationship between sample rate and standard error (SE) in estimating the 'true mean' CSH within the combined plot area (480 m^2) is illustrated in Figure 1. From this graph it can be seen that sampling rates can be reduced from 425 samples to eight, while still maintaining SE of mean CSH below 5%. This indicates that a considerable reduction in sampling rate, cost and time may be possible with a minor decrease in precision.

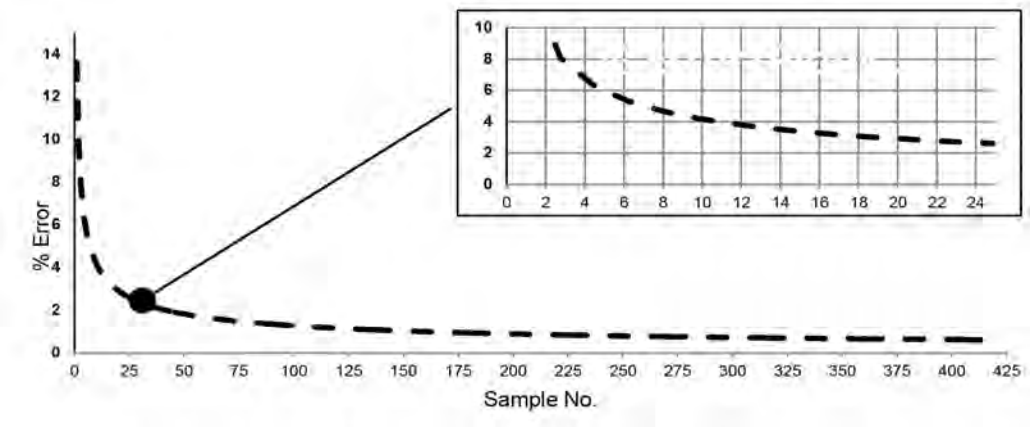

Figure 1. Simulated reduced sample rates plotted against standard error of mean CSH estimates, averaged across data collected for all 27 weeks

Initial evaluation by extrapolating these figures indicates mean CSH can be predicted to ± 10% SE using 189 samples ha^{-1}. Considering the time it would take to sample to this level of accuracy, it may not be economically feasible for carrying out day-to-day measurements. Further analysis is being conducted on full-sized grazed paddocks to optimise the sampling rate to a practical level to enable accurate management decisions to be made while simultaneously keeping measurement time to a minimum.

When the average actual recorded HM data for plot cuts were compared to the estimated HM figures derived from both preliminary linear and logarithmic equations (formulated as part of this study), along with the estimations made using the PastureBase Ireland (PBI) model, the PBI model resulted in the highest estimated error in comparison to the conceptual logarithmic model (Figure 2). PBI is a grassland management decision support tool developed by Hanrahan *et al.* (2017), which utilises a HM prediction model developed by Defrance *et al.* (2004). Model error varied considerably from month to month for all models, this indicates that the derivation of season specific models may increase prediction accuracy.

Figure 2. Average HM estimations from each model compared to HM actually recorded in Moorepark's Grassland Laboratory for each plot cut date

Regarding the application of NIRS to predict un-dried fresh grass quality, a range of spectral treatments were investigated and calibrations were ranked in order of the highest coefficient of determination (R^2) and lowest standard error of cross validation (SE_{CV}). The best performing calibrations ($R^2 > 0.93$, $SE_{CV} < 9.40$ g kg^{-1} and $R^2 > 0.89$, $SE_{CV} < 13.1$ g kg^{-1}DM for DM and CP, respectively) were selected for further expansion and validation. Results indicate that it is possible to accurately predict fresh grass quality using NIRS. This work is reported in detail elsewhere in these Proceedings.

Regarding the Remote sensing technologies, the results indicated that grass biomass can be estimated at a reasonable level by processing Sentinel-2 and Drone multispectral data using PLSR and at a moderate level using stepwise MLR. Red-edge, NIR and green wavelengths were identified as important for multispectral quantification of grass biomass. MCAR, MTVI and MNLI highly affected the biomass predictability of the drone multispectral data. Band 11 (centred at 1,610 nm) and band 12 (centred at 2,190 nm) considerably affected the biomass estimation of the Sentinel 2 model.

Conclusions

A framework and protocol for grass measurement optimisation has been identified, where the goal is to mitigate HM losses due to poor utilisation, while simultaneously maintaining labour costs at a minimum. An optimum level of accuracy where this goal may be achieved was estimated to be within the region of 5 - 10%. Potential for the development of an alternative more precise model to predict HM was evident. Potential justification for the development of independent seasonal models was also observed. It was possible to accurately predict the DM and CP composition of fresh grass using NIRS, without the need for laboratory pre-treatments. An NIRS fresh grass quality prediction equation would aid grass and feed management decisions and be highly beneficial to researchers, advisors and farmers. Regarding Remote Sensing technologies, grass biomass can be estimated at a reasonable level by processing Sentinel-2 and Drone multispectral data using PLSR and at a moderate level using stepwise MLR. The prototype GrassQ web platform combining all of the data from the aforementioned models is now operational and currently under evaluation. The developed prediction models included in GrassQ will be validated in 2019 and comparative analysis will be carried out on each measurement system. It is envisaged that GrassQ will highlight the benefits of targeted real-time precision grassland management.

References

Bailey, J., Higgins, A., and Jordan, C. (2000). Empirical models for predicting the dry matteryield of grass silage swards using plant tissue analyses. *Precision Agriculture, 2*(2): 131–145.

Chen, J. and Wang, X.Z. (2001). A new approach to near-infrared spectral data analysis using independent component analysis. *Journal of Chemical Information and Computer Sciences,* 41.4: 992–1001.

Cho, M.A., Skidmore, A., Corsi, F., van Wieren, S.E. and Sobhan, I. (2007). Estimation of green grass/herb biomass from airborne hyperspectral imagery using spectral indices and partial least squares regression." *International Journal of Applied Earth Observation and Geoinformation,* 9.4: 414–424.

Defrance, P., Delaby, L., and Seuret, J.M. (2004). Mieux connaître la densité de l'herbe pour calculer la croissance, la biomasse d'une parcelle et le stock d'herbe disponible d'une exploitation. *Proc. Rencontres autour des Recherches sur les Ruminants, 11* pp. 291–294. Paris.

Dillon, P., Hennessy, T., Shalloo, L., Thorne, F. and Horan, B. (2008). Future outlook for theIrish dairy industry: a study of international competitiveness, influence of international trade reform and requirement for change. *International Journal of Dairy Technology, 61*(1): 16–29.

French, P., Hanrahan, L., and Shalloo, L. (2015). Principles of sustainable dairy expansion. *Moorepark '15 Irish Dairying - Sustainable Expanasion*, 9–15.

Hanrahan, L., Geoghegan, A., O'Donovan, M., Griffith, V., Ruelle, E., Wallace, M., and Shalloo, L. (2017). PastureBase Ireland: A grassland decision support system and national database. *Computers and Electronics in Agriculture*, 136: 193–201.

Hutchinson, K.J., Scobie, D.R., Beautrais, J., Mackay, A.D., Rennie, G.M., Moss, R.A. and Dynes, R.A. (2016). A protocol for sampling pastures in hill country. *Journal of New Zealand Grasslands, 78*: 203–210.

Huyghe, C., De Vliegher, A., Van Gils, B. and Peeters, A. (2014). Executive summary. In T. Jones (Ed.), *Grasslands and herbivore production in Europe and effects of common policies* (pp. 7-13). Versailles Cedex, France: Editions Quae.

Jordan, C., Shi, Z., Bailey, J.S. and Higgins, A.J. (2003). Sampling strategies for mapping 'within-field' variability in the dry matter yield and mineral nutrient status of forage grass crops in cool tmperate climates. *Precision Agriculture, 4*(1): 69–86.

Fei, L., Mistele, B., Hu, Y., Chen, X. and Schmidhalter, U. (2014). Reflectance estimation of canopy nitrogen content in winter wheat using optimised hyperspectral spectral indices and partial least squares regression. *European Journal of Agronomy,* 52: 198–209.

O'Donovan, M., Dillon, P., Rath, M. and Stakelum, G. (2002). A Comparison of Four Methods of Herbage Mass Estimation. *Irish Journal of Agricultural and Food Research, 41*(1): 17–27.

Park, B, Chen, Y.R., Hruschka, W.R. Shackelford, D. and Koohmaraie, M. (1998). Near-infrared reflectance analysis for predicting beef longissimus tenderness. *Journal of Animal Science*, 76.8: 2115–2120.

Sanderson, M.A., Rotz, C.A., Fultz, S.W. and Rayburn, E.B. (2001). Estimating forage mass with a commercial capacitance meter, rising plate meter, and pasture ruler. *Agronomy Journal, 93*(6): 1281–1286.

Shalloo, L., Dillon, P. and Murphy, J.J. (2005). A comparison of three systems of milk production with different land use strategies. Paper presented at the Satellite Workshop of the XXth International Grassland Congress, Cork, Ireland.

Webster, R. and Lark, M. (2012). Efficiency, economy and logistics. In Routledge (Ed.), *Field sampling for environmental science and management* (pp. 56). Milton Park, Abingdon, Oxon, UK: Routledge.

Analysis of the internal environment of the domestic duck house and assessment of moisture generation from the litter

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Abstract

The total production of livestock in South Korea reached about 17 billion USD in 2016, which was about 44%, of the total agricultural production. Duck industry, which is one of the fast-growing industries, occupied 6th in the livestock industry in 2017. However, most of the duck houses are conventional facilities, which have been converted from plastic greenhouses. The conventional facilities are vulnerable to control humidity, which is a very important factor directly related to disease, because of low insulation properties. The moisture generation from the litter of a duck house is one of the main factors affecting internal humidity. However, there is no previous study for quantitatively analysing the amount of moisture generation. In addition, there were few researches on environmental control of duck houses combining ICT technology. Therefore, the objective of this study is to analyse the internal environment of the domestic duck house and evaluate the moisture generation from the litter. For the two types of duck houses, which are mechanically ventilated and naturally ventilation duck houses, environmental conditions inside and outside of duck houses are monitored. Inside duck houses are monitored for air temperature, humidity, and ventilation rates were observed and for outside air temperature, humidity, wind velocity, rainfall, and solar radiation were observed. Based on monitored data, problems relating to environmental control were analysed. In addition, the experimental chamber was produced for observing moisture generation from the litter according to air temperature, humidity, wind velocity near litter, and water contents of the litter. The statistical analysis was conducted for deriving the regression equation.

Keywords: duck house, environmental control, environmental monitoring, litter

Introduction

The total production of livestock in South Korea reached about 17 billion USD in 2016, which was about 44% of the total agricultural production. Duck industry, which is one of the fast-growing industries, occupied 6th in the livestock industry of South Korea in 2017. However, most of the duck houses are conventional facilities, which have been converted from plastic greenhouses. The conventional facilities are vulnerable to control humidity, which is a very important factor directly related to disease, because of low insulation properties. The moisture generation from the litter of a duck house is one of the main factors affecting internal humidity. However, there is no previous study for quantitatively analysing the amount of moisture generation. In addition, there were few researches on environmental control of duck houses combining ICT technology. Therefore, the objective of this study is to analyse the internal environment of the domestic duck house and evaluate the moisture generation from the litter.

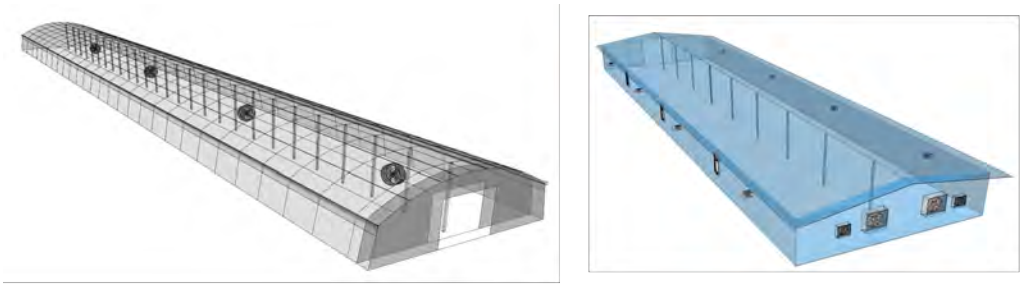
Material and methods

Experimental duck house

The experiments were conducted at two types of duck houses with naturally and mechanically ventilated systems which are located in Sinbuk-myeon, Yeongam-gun, Jeollanam-do Province (126°64´E, 34°89´N).

Figure 1. The experimental site in which the naturally and mechanically ventilated duck houses were located

The naturally ventilated duck house was 10 m in width, 70 m in length, 2.0 m in eave height, and 3.5 m in ridge height. The mechanically ventilated duck house was 12 m in width, 45 m in length, 2.9 m in eave height, and 3.8 m in ridge height. The naturally and mechanically ventilated duck houses were fundamentally made of 0.15 mm plastic film and 100 mm thick EPS panel. There are two winch curtain openings (1.0 m × 70 m) at the side wall of naturally ventilated duck house. There are six slot openings (0.3 m × 0.5 m), two 50 inch fans and 30 inch fans for mechanical ventilation in mechanically ventilated duck house. In these two duck houses, litter is continuously used as the bedding material without replacement. The breeding period is 40 - 45 days.

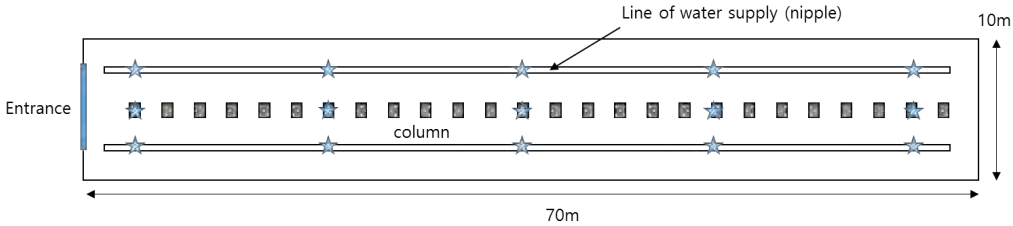


[Naturally ventilated duck house] [Mechanically ventilated duck house]

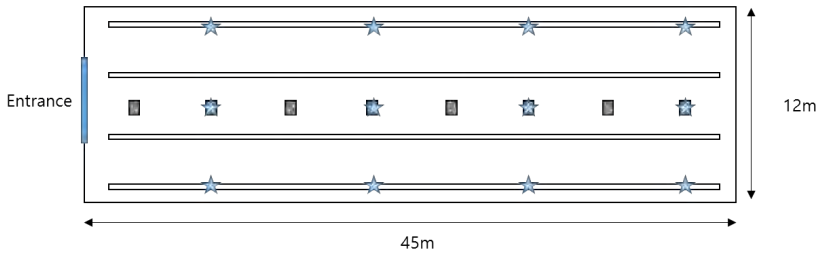
Figure 2. Schematic information of the target duck houses

Monitoring data of internal and external environments of the experimental duck houses

The environments in a duck house such as air temperature, humidity, and so on are related to the growth rate of the ducks and the quality of the products. Therefore, it is very important to properly control the internal environment of duck houses. The internal air temperature and relative humidity of duck houses were observed at intervals of one second using air temperature and relative humidity sensors (HTX 75c, Dotech Inc.) which error range of air temperature and relative humidity are ± 0.3 °C and 2.0%. The 15 and 12 sensors were installed at height of 1.5 m inside the naturally and mechanically ventilated duck houses, respectively. A potable weather station (WatchDog 2900ET, Spectrum Technologies) was installed on the roof of the control room for monitoring outside environments such as the wind direction, wind speed, relative humidity and air temperature at intervals of 10 minutes. The measured data at June 2018 and February 2019 were used for seasonal analysis.



[Naturally ventilated duck house]



[Mechanically ventilated duck house]

Figure 3. Top view of naturally and mechanically ventilated duck houses and sensor locations for monitoring internal air temperature and relative humidity

Airflow rate at the mechanically ventilated duck house is one of the major factors for maintaining optimal environment. When controlling internal environment for growing ducks, it is essential to monitor airflow rate of the mechanically ventilated duck house. Air flow rate of the mechanically ventilated duck house was observed using electrometer and AC clamp sensors. The airflow rates were estimated using the amount of electric current when fans were operated.

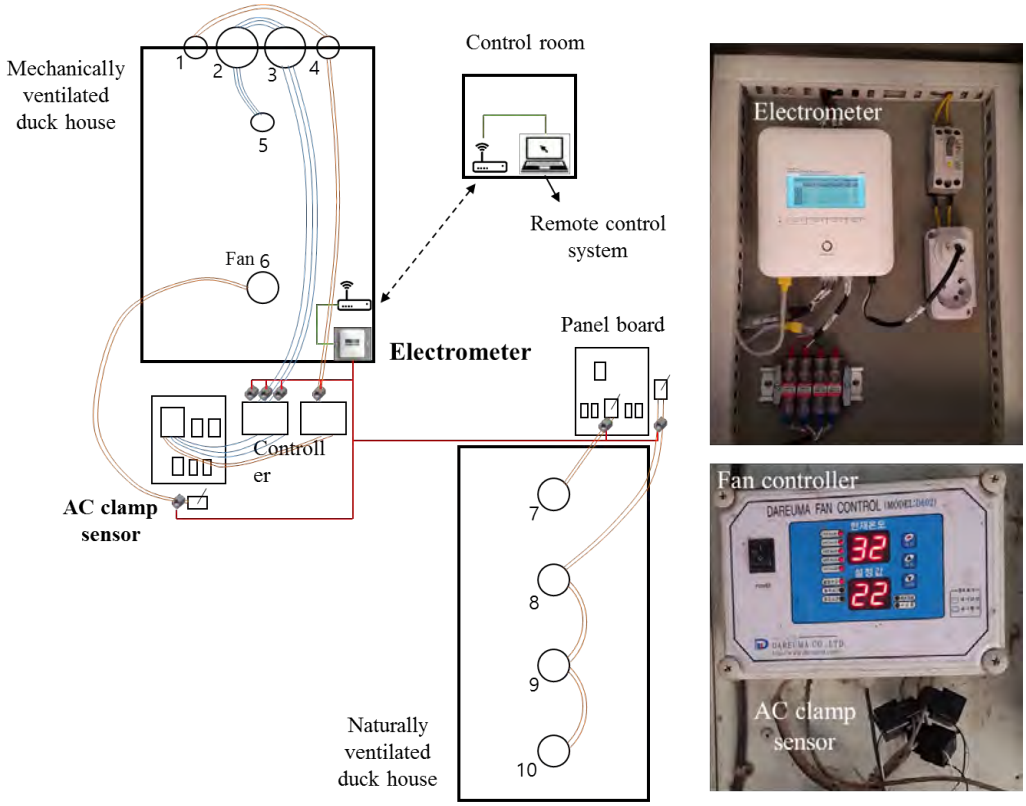
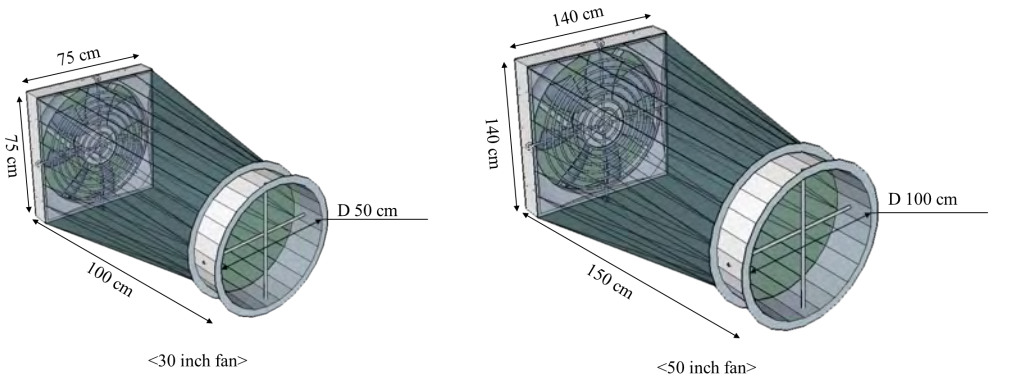


Figure 4. Diagram to monitor the amount of electric current using electrometer and AC clamp sensors when fans were operated

The field experiments were conducted to measure the actual overall ventilation rate of the mechanically ventilated duck house. The airflow meters were manufactured in-house according to the size of fans. The actual airflows of fans were observed using micro manometer (DP-CALC, TSI) according to the opening configuration and the control level of fans.

Lab experiments for observing moisture generation from the litter

Lab experiments were conducted to quantify the evaporation rate of water from the litter samples according to wind velocity (1.5, 2.0, 2.5 m/s), air temperature (15, 25, 35 °C), relative humidity (40, 60 80%), water contents (10, 35, 60%). The air temperature and relative humidity were controlled with the temperature and humidity controlled chamber. The lab experiment was conducted following the method of previous study (Dunlop *et al.*, 2015). The experimental procedure is shown in the Figure 6.



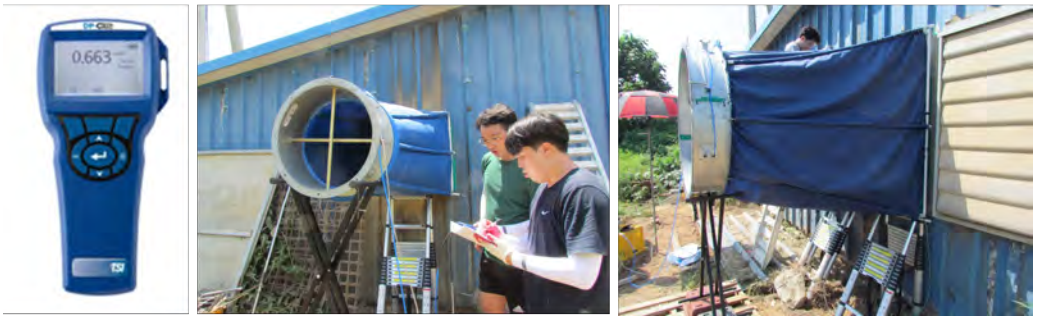


Figure 5. Field experiment for measuring actual airflow rate according to pressure load by opening configurations

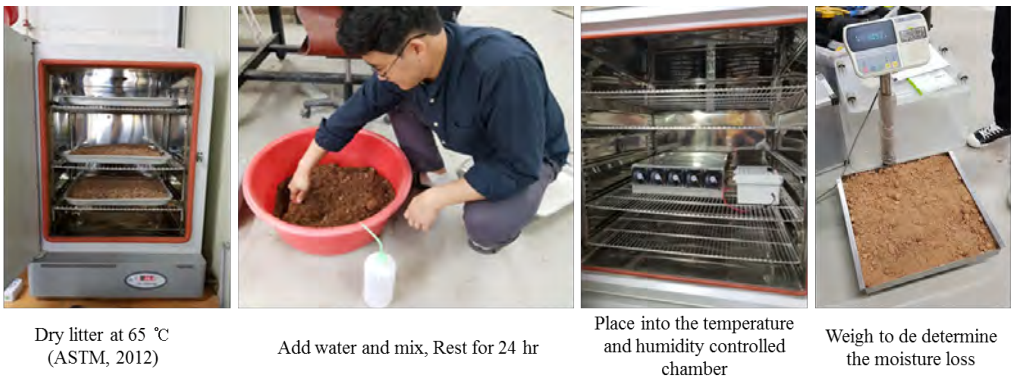


Figure 6. Experimental procedure for quantifying the evaporation rate of water from the litter samples

Results and discussion

Analysis of monitoring data

In June, air temperatures inside the naturally and mechanically ventilated duck houses were maintained close to the proper air temperature (Rural Development Administration of South Korea, 2016). However, air temperature inside the mechanically ventilated duck house was lower than 20 °C at nighttime. Additionally, the air temperature in a mechanically ventilated duck house was always lower than outside air temperature.

As environmental variables were fluctuated at naturally ventilated duck houses, the homogeneity of environments in mechanically ventilated duck houses was higher than those in naturally ventilated duck houses.

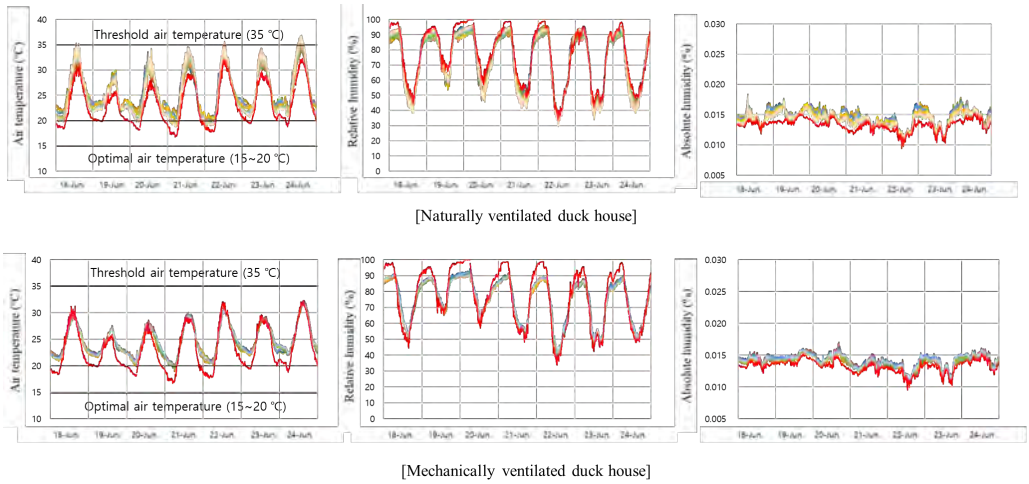


Figure 7. The result of analysing monitoring data (red line: external environments)

The airflow rates were monitored using electrometer and AC clamp sensors. The 50 inch fans were operated at daytime for cooling the air temperature inside a mechanically ventilated duck house. The 30 inch fans were controlled stepwise to meet the proper air temperature. The air exchange rate of a mechanically ventilated duck house was a little low as the range of 0.1 - 0.6 min^{-1}.

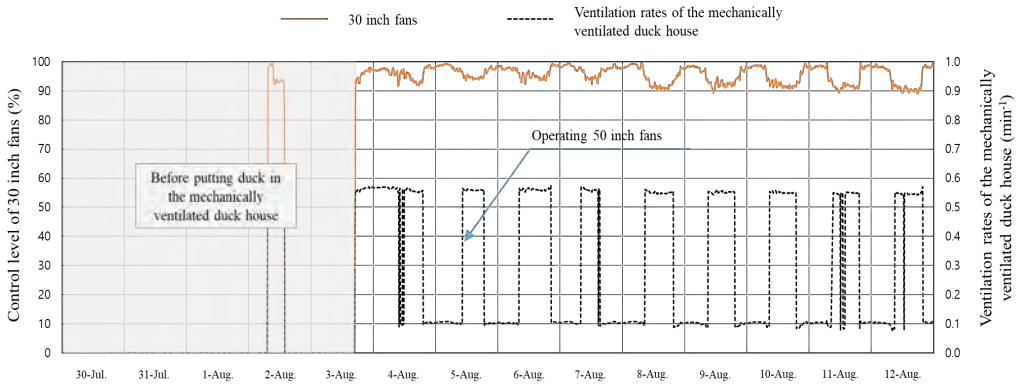


Figure 8. The result of monitoring ventilation rate of the mechanically ventilated duck house

Analysis of observing moisture generation from the litter

The regression analyses were conducted to estimate evaporation rate of litter from environmental variables. As a result of regression analysis, regression equation was derived as follows. The accuracy of estimating evaporation rate of litter was reasonable because the determination coefficient was calculated as 0.76. Additionally, each environmental variable was verified to be independent because variance inflation factor of all environmental variables was lower than 10.

Water generation= -1.31 + 0.25 × Air temperature - 0.20 × Relative humidity + 10.86 × Water contents + 7.74 × velocity

Table 1. Regression analysis for estimating evaporation rate of litter from environmental variables (air temperature, relative humidity, water contents, velocity)

Multiple R	0.76		Adjusted R	0.71
F-statistic	16.27		p-value	3.29×10^{-6}
	Estimate	**Std. Error**	**t value**	**Pr (>|t|)**
(Intercept)	-11.31	4.65	-2.43	0.02415 *
Air temperature	0.25	0.07	3.79	0.00108 **
Relative humidity	-0.20	0.04	-4.53	0.00018 ***
Water contents	10.86	2.29	4.74	0.00011 ***
Velocity	7.74	1.89	4.10	0.00051 ***

Signif. codes : *** 0.001 ** 0.01 * 0.05

In order to improve the accuracy of multiple regression equation, partial vapor pressure which is directly related to water evaporation was applied instead of relative humidity. As the determination coefficient was calculated as 0.77, the accuracy of regression model was slightly improved.

Water generation = -21.4 + 0.525 × Air temperature - 3.48×10^{-3} × Partial vapor pressure + 10.9 × Water contents + 7.75 × velocity

Table 2. Regression analysis for estimating evaporation rate of litter from environmental variables (air temperature, partial vapor pressure, water contents, velocity)

Multiple R	0.77		Adjusted R	0.72
F-statistic	17.31		p-value	2.03×10^{-6}
	Estimate	**Std. Error**	**t value**	**Pr (>|t|)**
(Intercept)	-2.14×10^{1}	4.21	-5.07	5.08×10^{-5} ***
Air temperature	-5.25×10^{-1}	1.06×10^{-1}	4.96	6.65×10^{-5} ***
Partial vapor pressure	-3.48×10^{-3}	7.33×10^{-4}	-4.75	0.000109 ***
Water contents	1.09×10^{1}	2.24	4.86	8.43×10^{-5} ***
Velocity	7.75	1.84	4.20	0.000399 ***

Signif. codes : *** 0.001 ** 0.01 * 0.05

Conclusions

In this study, environmental conditions inside and outside of duck houses were monitored for the two types of duck houses which are mechanically ventilated and naturally ventilated duck houses. Inside duck houses, air temperature, humidity, and ventilation rate were observed and for outside air temperature, humidity, wind velocity, rainfall, and solar radiation were observed. Based on monitored data, problems related to environmental control were analysed. In addition, the experimental chamber was produced for observing moisture generation from the litter according to air temperature, humidity, wind velocity near litter, and water contents of the litter. Finally, the regression equations were derived to estimate the evaporations from litter.

Acknowledgements

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References

Dunlop, Mark W., Blackall, Patrick J., & Stuetz, Richard M. (2015). Water addition, evaporation and water holding capacity of poultry litter. *Science of the Total Environment* 538: 979–985.

Rural Development Administration of South Korea (2016). Guide for agricultural business management: Duck management, South Korea.

Evaluation of two roof insulation materials poultry houses thermal environment and layer hen performance in summer

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Abstract

In confined poultry buildings, the thermal insulation performance of building construction can have positive impacts on the housing comfortable temperature environment. The roof and consequently the ceiling as the main part of poultry house building envelope receives the most radiant heat under high solar insolation. Stronger convection heat transfer between roof inner surface and air increased temperature variations along vertical directions in houses, and higher temperature occurs near the roof of poultry house, resulting in heat stress for the birds near the ceiling. Heat stress has resulted in significant economic losses in large-scale egg productions due to the decrease of egg production rate, the increase of hen mortality and the cost of thermal environment control. Experiments were conducted in two poultry houses with different roof types, to determine the effects of roof insulation on thermal environment and egg production rate in hot weather. Results showed that: Temperature and relative humidity fluctuations in experimental house were smaller than that in control house, and temperature in control house was 2.3 °C higher than that in experimental house; The level of heat stress in control house was higher than that in the experimental house. The normal level of temperature and humid in the former was lower by 15.7% compared with that in the latter; The average egg production rates in control poultry house and experimental house were 92.5% and 94.0%, respectively, and the average egg weight in control house was 1.9 g less than that in experimental house.

Keywords: radiation, temperature, humidity, heat stress, cooling load, laying performance, mortality

Introduction

Birds are usually kept in insolated structures constructed by people (Olgun *et al.,* 2007) and the basic aim in poultry production is to obtain the yield in a desirable level at the lowest cost as in other husbandry fields (Ndukwu *et al.,* 2015). Maintaining adequate environment for the hens is essential to ensuring the hen's well-being, maximum productivity, and efficient feed utilization (Zheng *et al.,* 2018). Karaman, *et al.* (2012) mentioned that heat loss through structural elements via conduction, convection, and radiation or heat gains should be kept at desirable levels to provide optimum climate environmental conditions in poultry houses. Researchers revealed significant insulation problems in animal housing especially over roofs developed a finite difference solution, considering conduction, storage, sensible heat production, and solar heat transfer effects for a non-ventilated structure (Albright *et al.,* 1974). Results indicate a significant effect due to solar energy in increasing inside temperature and in producing an earlier daily peak inside temperature. Webster A B *et al.* (2000) indicated that if there are variations of temperature according to different locations within the layers closed house, then birds will consume lesser or greater amounts of nutrients than required, hence, egg size will differ greatly; Abbas, *et al.* (2011) was concluded that fluctuation of the temperature inside the closed poultry house will affect the performance of laying hens. But there is little-published information on the interior thermal environment of different construction materials closed layer houses in

relation to flock production characteristics. This experiment was carried out to observe the impacts of different construction materials on thermal environment conditions of closed layer houses and in relation to production performance characteristics, temperature and hen performance was monitored.

Material and methods

Experimental layer houses

The layer houses are oriented along East-West direction and are 90 m × 12 m × 3.5 m (Length × Width × Height), located in Chengdu (104°20'E,30°29'N), Sichuan Province in China, and the maximum distance from the floor to the roof is 4.5 m, with a capability of hosting up to 30,000 laying hens. The houses held five rows of "H" batteries with four tiers of cages per battery. The house A wall used 370 mm plaster bricks and roof used 200 mm aerated concrete. For wall and ceiling construction, 100 mm and 200 mm mineral cotton sandwich colour steel shelf was used in the house B. Two commercial laying hen houses used concrete floors. Ten exhaust fans with a diameter of 1.40 m are installed on the opposite gable wall in each house. Ventilation practices were tried to be kept at same levels in poultry houses during the research period. The two poultry houses wet-pads are 10 m × 0.10 m × 3.0 m (Length × Thickness × Height) in gable wall and 2 m × 0.10 m × 2.0 m (Length × Thickness × Height) in each sidewall end. Rectangular inlets were distributed on sidewalls, with dimensions of 0.50 m × 0.30 m × 0.30 m (Width × Height × Thickness) and the installation height of 2.85 m. The main characteristics of the two houses are listed in Table 1.

Table 1. Characteristics of the two commercial poultry houses

Descriptive parameter	House A	House B
House length × width (m)	90 × 12 × 3.5	90 × 12 × 3.5
Sidewall and ridge height (m)	3.5/4.5	3.5/4.5
House orientation	E-W	E-W
Wall area (m^2) and coefficient (w/(m^2·K))	1,095/1.49	1,095/0.73
Roof area (m^2) and coefficient (w/(m^2·K))	679/0.86	679/0.41
Floor area (m^2) and coefficient (w/(m^2·K))	1,080/0.46	1,080/0.41
Number of tiers and row of cages	4 tiers/4 rows	4 tiers/4 rows
The actual number of birds (n)	28,965	28,895
Birds age begin and end (week)	19-22/39-42	19-22/39-42
Ventilation type	Mechanical	Mechanical
Manure collection method	Belts	Belts
Type of inlets	Flap baffles	Flap baffles

Temperature and relative humidity monitoring

Temperature and relative humidity in the two poultry houses and outside environment were measured with portable temperature and humidity data loggers (HOBO Pro Series Temp/RH logger, Onset, Bourne, MA, US), with a range of -40-70 °C and an accuracy of 0.2 °C for air temperature, a range of 0-100% and an accuracy of 3% for relative humidity. The temperature and humidity data were collected during summer and winter period, from 1–28 July 2017, 1–28 December 2017 and measured at 30 testing locations in house A and house B. They were positioned on each cage row as shown in Figure 1. For each house, the sensors were distributed to three groups, ten loggers were 22 m from the row front ends, ten sensors were at the row centers and the remaining loggers were 24 m from the rows ends. These loggers were considered to represent Front, Middle, and Rear areas of the house, respectively. Each temperature and relative humidity data loggers were fixed to the side of the second and fourth tiers cages at the breadth height of the hens counting from the bottom with a height of 1.05 m (Lower) and 2.25 m (Upper), respectively. The air temperature and relative humidity which were measured in each of experimental days were was considered as a replicate.

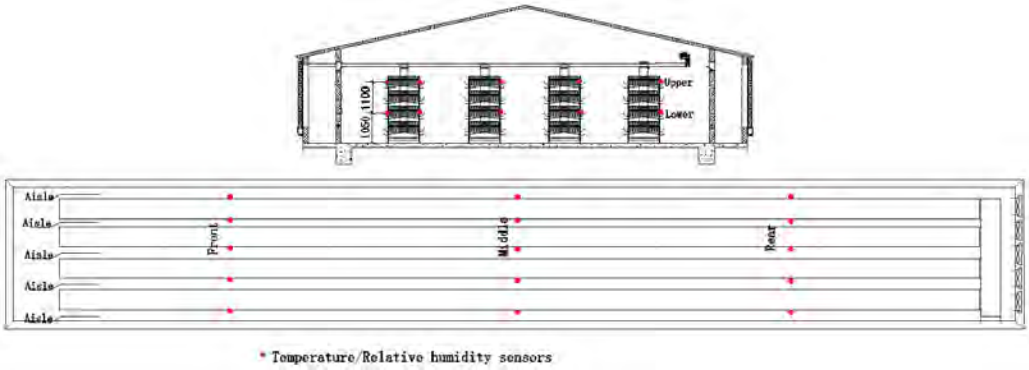


Figure 1. Schematic view of the temperature and humidity testing sensors along vertical and horizontal directions in the poultry house. Front, Middle, and Rear sensors were 22 m, 44 m, and 88 m away from the gable wall without fans, respectively. Lower and Upper sensors were at the height of 1.05 m and 2.25 m, respectively. • Temperature and humidity testing sensors locations in house A and B

Layer performance monitoring

To analyse effects of thermal environment conditions on poultry performance, the following data were collected at 19 - 22 weeks (1–28 July) and 39 - 42 weeks (1–28 December) in production cycle: the number of layers at start and end, feed consumption per day, body weight, mortality per day, egg production, egg weight, broken egg, dirty egg and soft eggshell. Hy-Line W-36 have housed six birds per cage. All the eggs were weighted and the 15 birds were weighted per row randomly at the end week, and feed consumption, mortality, egg production, broken egg, dirty egg and soft eggshell were recorded data per day.

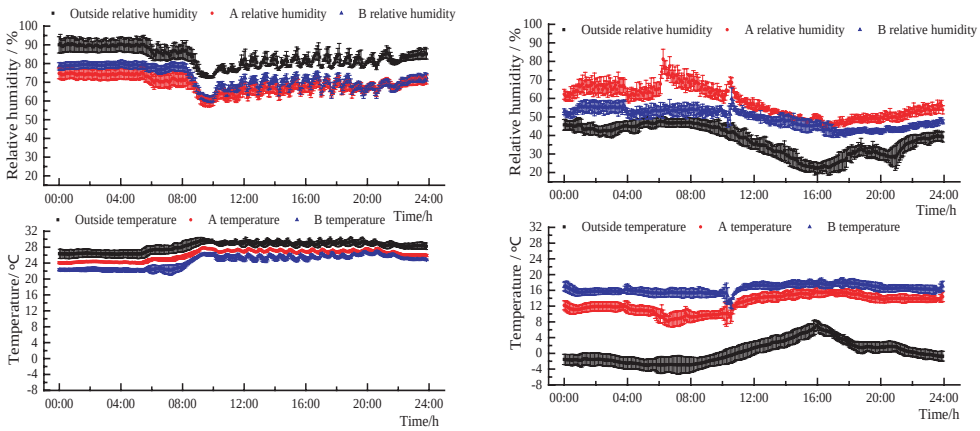
Statistical Analyses

The average, maximum, and minimum values and standard deviation (STD) of air temperature and relative humidity at each testing location were measured in this experiment. Data obtained from the experiment were analysed by analysis of variance using Origin 9.0 (Origin Lab, Northampton, MA, US), and the significant differences between means were assessed using Least Significance Difference (LSD).

Results and discussion

Temperature and relative humidity in two poultry houses

The mean outdoor and indoor air temperatures, relative humidity in poultry house A and house B were 28.1±0.84 °C, 26.1±0.18 °C, 24.5±0.41 °C and 83.5±2.61%, 68.8±2.62%, 72.3±1.84% in summer, and 0.3±0.51 °C, 12.6 ±1.13 °C, 16.3±0.92 °C and 37.5±3.34%, 58.1±2.54%, 59.3±2.26% in winter, respectively. Diurnal variation of outdoor and poultry house A and B air temperature and relative humidity in summer and winter were shown in Figure 2. Two poultry houses indoor air temperature and relative humidity had a parallel trend with outdoor temperature and relative humidity. The indoor air temperature ranged from 23.9–27.8 °C in summer and 8.1–12.7 °C in winter in poultry house A and ranged from 22.2–24.4 °C in summer and 13.7 °C to 16.4 °C in winter in poultry house B, while the mean outside temperature ranged from 26.2–30.6 °C in summer and -3.1–7.0 °C in winter. The highest mean indoor temperatures were observed at 10:00 in the two poultry houses. Wang Y *et al.* (2017) reported than the optimum temperature and relative humidity for caged poultry should be ranged as 13-27 °C and 60-65%. The results showed that in poultry house B provided homogenous air environment than the poultry house A in the summer and winter, the maximum fluctuation in average air temperature in consecutive 30 days was reduced to 2.0 °C in summer and 2.7 °C in winter.



(a) (b)

Figure 2. Diurnal variation of the air temperature and relative humidity in outside and poultry house A and B in period. (a) Diurnal variation of air temperature and relative humidity in summer in outside and poultry house A and B; (b) Diurnal variation of air temperature and relative humidity in winter in outdoor and poultry house A and B

Temperature and relative humidity in two poultry houses

Laying performance and mortality variations were related to variations of inner temperature and relative humidity in the poultry houses, which are presented in Table 2. Comparisons of the recorded showed that egg weights were a significant difference in the different poultry house in summer and winter, and egg weight in the poultry house A was larger in the poultry house B in winter. No significant difference in mortality, broken egg, dirty egg and soft eggshell were found among the two poultry houses in this research. A significantly increased bird body weight at 19–22 weeks and 39–42 weeks were obtained in the two houses. Also, significantly increased feed consumption were recorded at 19–22 weeks and 39–42 weeks. Compared with the egg production, egg productions were

higher in the poultry house B than poultry house A (81.8% and 96.9% vs 79.3% and 96.3%). Similarly, the feed consumptions were statistically significant between the two different construction materials poultry houses and were significant between the two types construction materials poultry houses. Also, the feed consumptions were lower in the poultry house B than poultry house A (110.2% vs 113.2%) in winter. The results were in line with Webster A B *et al.* (2000) that correlations of average temperatures with performance data recorded at the same sites show that egg weight variation within the house was significantly associated with in-house variation of temperature and the relationship was negative, indicating that egg weights were lower in areas with higher temperatures and larger variation of temperature in different places within the closed layers house would lead to marked variation in feed consumption and hen birds will consume lesser or greater amounts of nutrients than required, hence, egg size differs greatly.

Table 2. The productive performance of layer in the two different construction materials closed layer houses

Time	Parameters	House A	House B	LS
Summer	Mortality (%/day)	0.01±0.36	0.01±0.40	NS
(19-22 weeks)	Feed consumption (g/bird/day)	94.2±1.12	93.6±1.09	**
	Egg production %	79.3±0.89	81.8±0.54	**
	Egg weight (g)	49.2±1.7	50.2±1.6	*
	Broken eggs (%/day)	0.46±0.18	0.47±0.09	NS
	Dirty eggs (%/day)	0.13±0.97	0.13±0.88	NS
	Soft eggshell (%/day)	0.03±0.29	0.02±0.48	NS
	Body weight at 19 weeks (g)	1,403.4±7.8	1,484.8±3.3	*
	Body weight at 22weeks (g)	1,620.9±3.8	1,669.9±4.1	*
Winter	Mortality (%/day)	0.02±0.76	0.01±0.55	NS
(39-42 weeks)	Feed consumption (g/bird/day)	113.2±1.97	110.2±1.82	**
	Egg production %	92.5±0.28	94.0±0.43	**
	Egg weight (g)	61.7±1.5	59.9±1.1	*
	Broken eggs (%/day)	0.51±0.27	0.57±0.03	NS
	Dirty eggs (%/day)	0.17±0.38	0.16±0.26	NS
	Soft eggshell (%/day)	0.03±0.99	0.03±0.56	NS
	Body weight at 39 weeks (g)	1,800±2.2	1,810±7.2	*
	Body weight at 46 weeks (g)	1,817±3.1	1,822±5.8	*

* means a significant difference in $P < 0.05$ level; ** means the highly significant difference in $P < 0.01$ level; NS means no significant difference.

Conclusions

In this study, the effect of different construction materials on the inner thermal environment was researched and impact on the poultry performance was evaluated. Temperature and humidity fluctuations in experimental house were smaller than that in control house, and temperature in control house was 2.3 °C higher than that in experimental house. The level of heat stress in control house was higher than that in experimental house in summer, and

the normal level of temperature and humid in the former was lower by 15.7% compared with that in the latter; The average egg production rates in control poultry house and experimental house were 92.5% and 94.0%, respectively, and the average egg weight in control house was 1.9 g less than that in experimental house.

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References

Albright, L.D., and Scott, N.R. (1974). An analysis of steady periodic building temperature variations in warm weather Part I: A Mathematical Model. *Transactions of the ASABE* 17(1): 88–92.

Olgun, M.M., Yavuz, Ç., and Polat, H.E. (2007). Determining of heat balance design criteria for laying hen houses under continental climate conditions. *Building and Environment,* 42(1): 355–365.

Ndukwu, M.C., and Manuwa, S, I. (2015). Techno-economic assessment for viability of some waste as cooling pads in evaporative cooling system. I*nternational Journal of Agricultural & Biological Engineering,* 8(2): 151–158.

Macmanus, C. (2015). Techno-economic assessment for viability of some waste as cooling pads in evaporative cooling system. *International Journal of Agricultural & Biological Engineering,* 8(2): 151–158.

Zhao, Y., Xin, H., Shepherd, T.A., Hayes, M.D., and Stinn, J.P. (2013). Modelling ventilation rate, balance temperature and supplemental heat need in alternative vs. conventional laying-hen housing systems. *Biosystems Engineering,* 115(3): 311–323.

Karaman, S. (2012). Variation of thermal conditions and heat-moisture balance in caged-poultry houses with different roof insulations. *Journal of Animal & Veterinary Advances,* 11(13): 2359–2366.

Wang, Y., and Li, B. (2017). Analysis and experiment on thermal insulation performance of outer building envelope for closed layer house in winter. *Transactions of the Chinese Society of Agricultural Engineering,* 33(7): 190–196.

Characterisation of key factors for dust generation in broiler houses

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Abstract

Particulate matter within broiler houses deteriorates indoor air quality and causes various health problems in both farmers and broilers. To introduce a proper dust control strategy, the dust concentration and the mechanisms of dust generation according to a complicated combination of environmental variables should be understood. In this work, long-term dust monitoring in mechanically and naturally ventilated broiler houses was carried out to determine the key factors affecting dust generation. The micro-climatic factors, such as air temperature and humidity, outdoor weather conditions, age of broilers, activity of broilers, water contents of bedding materials, and ventilation rate, were simultaneously measured to conduct statistical analyses. The ventilation rate of each broiler house was numerically computed using a computational fluid dynamics model. From the observations, relatively high dust concentrations were obviously measured when broiler farmers entered the facility; this was due to the increase in the broiler activity, especially in the autumn and winter seasons when a minimum ventilation rate was generally adopted. Those dust concentration values easily exceeded the occupational exposure limits per their size fractions. Based on statistical analysis, the activity of broilers was found to be a key factor for dust generation in both experimental broiler houses; however, controlling the humidity level may be a practical method to control the generation of the larger fractions, such as inhalable dust, when considering the field-applicability of each variable.

Keywords: broiler, inhalable dust, monitoring, respirable dust

Introduction

Over the past several years, many researchers have expressed their concerns about the poor working conditions in livestock facilities (Cambra-Lopez *et al.*, 2010). Broiler farmers are exposed to substantially higher levels of dust, NH_3, and odorous matters. Among the pollutants, dust is strongly relevant to the deterioration of the health of broiler farmers and animals (Takai *et al.*, 1998). From dose-response and epidemiological studies, it has been proven that livestock farmers have a high prevalence of coughing, wheezing, allergic and non-allergic rhinitis, declined lung function, ODTS, bronchitis, and asthma when compared to individuals working in other industries (Basinas *et al.*, 2012). Dust can also cause various respiratory symptoms and increase the mortality rate for animals (Al Homidan *et al.,* 1996).

Kwon *et al.* (2016) reported that the dust concentration inside livestock houses are governed by various factors such as the species, age of animals, rearing density, feeding and breeding management, ventilation (seasonal changes), temperature and humidity. Many studies within the fields of livestock industry have shown a single correlation between pollutant matter and environmental factors. Banhazi *et al.* (2008) conducted comprehensive studies that statistically investigated various factors related to dust in order to determine the key factors for the generation of airborne pollutants inside pig houses. Although their studies considered many factors, such as the facility type, rearing stage, hygiene status, and micro-climatic factors, they were based on short-term and broad observations made at each experimental farm. In addition, a quantitative approach for the ventilation rate was

not included in their studies. Quantitative evaluation of the ventilation rate of livestock houses is very challenging due to the difficulty of controlling and measuring the invisible airflow patterns. Here, the application of a numerical model such as computational fluid dynamics (CFD) technique with a tracer gas decay method can be a kind of solution to quantitatively evaluate the ventilation rate of agricultural facilities.

In this study, intensive and long-term monitoring of the aerial dust, including the total suspended particulate (TSP), PM10, inhalable and respirable dusts, was conducted in mechanically- and naturally-ventilated broiler houses, which are the commercial types of broiler houses found in South Korea. To ensure a comprehensive approach, various factors, such as the air temperature, humidity, ventilation rate, age of broilers, working activities of broiler farmers, and water content levels of bedding materials, were simultaneously measured. The CFD technique was adopted to quantitatively calculate the ventilation rate of the experimental broiler houses using the TGD method. From the experimental and numerical data, we attempted to determine the key factors affecting dust generation in broiler houses using a multiple regression statistical model.

Material and methods

Experimental broiler houses

Experimental farms are located in Jeongeup City, South Korea. The size of the mechanically-ventilated (MV) broiler house was 15.0 m wide, 85.0 m long, 3.2 m high at the eaves, and 6.3 m high at the ridge (Figure 1). 14 tunnel exhaust fans with a capacity of 26,500 CMH for each fan and plate openings with a length of 24.45 m and a height of 1.58 m were located at both side walls near the main entrance door. Meanwhile, three-side exhaust fans (33,000 CMH for each fan) and a number of baffles (1.25 m long and 0.43 m high) used for cross ventilation in the winter season. 30,000 heads of broilers were raised in the facility, resulting in a rearing density of 23.53 heads m^{-2}. In the case of the naturally-ventilated (NV) broiler house, the facility used a combination of natural ventilation with winch curtain openings and mechanical ventilation with eight exhaust fans during the summer season. However, mechanical ventilation with eight exhaust fans and a number of pipe inlets was adopted during the winter season and during the early rearing stages of the broilers. The size of the NV broiler house was 11.0 m wide, 85.5 m long, 1.5 m high at the eaves, and 4.5 m high at the ridge (Figure 2). Four exhaust fans (6,020 CMH for each fan) were installed at both the front and back side walls to achieve additional ventilation. For ventilation operation during the winter season, 90 PVC pipe inlets with a diameter of 0.1 m and a length of 1.95 m were installed along the slope beneath the roof. Twenty five thousand heads of broilers (rearing density of 26.58 heads m^{-2}) were raised in this facility.

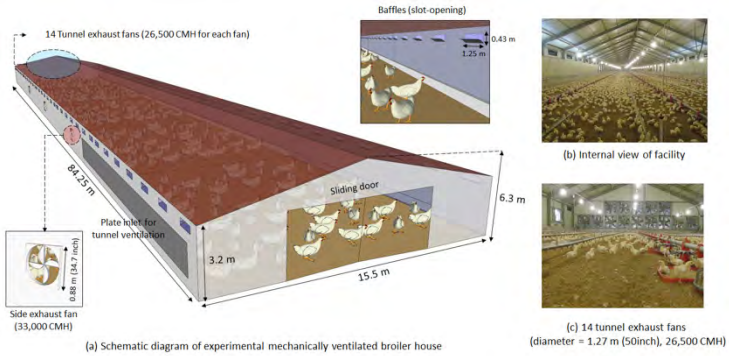

Figure 1. Schematic diagram of experimental mechanically ventilated broiler house

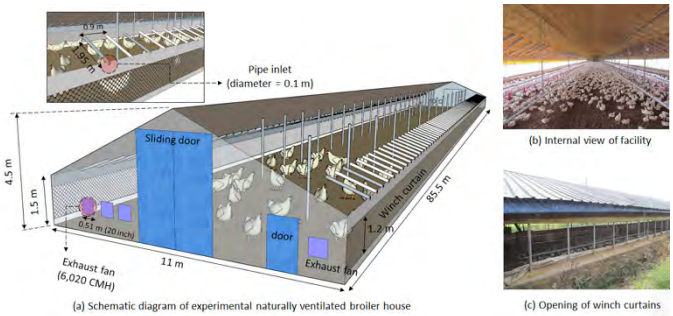

Figure 2. Schematic diagram of experimental naturally ventilated broiler house

Experimental monitoring of aerial dust in broiler houses

The experiment was regularly conducted according to the rearing stage of broilers (e.g. ages of 1, 2, and 4 weeks) for 13 months. The pre-weighed polytetrafluoroethylene membrane filters (SKC Inc., USA) were inserted in a three-stage polystyrene cassette (SKC Inc.) for TSP, while PM10 was sampled in a PEM sampler (SKC Inc., 10 μm sampling cut-off diameter). The flow rates for the TSP and PM10 were 2 and 4 l min^{-1} for 8 h, respectively. Dust sampling instruments were installed at a height of 1.5 m. Concentration of the TSP and PM10 were calculated with the gravimetric method.

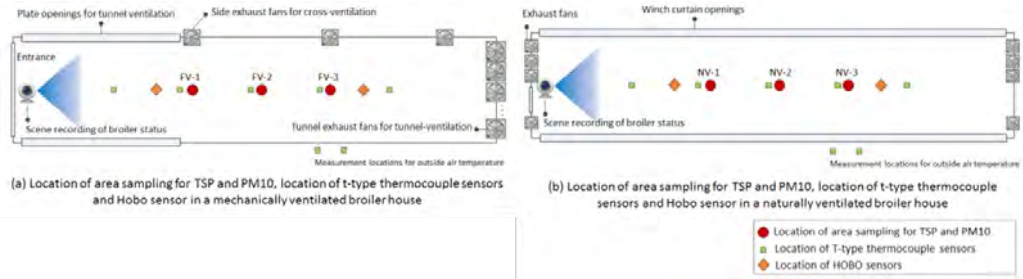

Figure 3. Sampling locations for dust and micro-climatic factors

The concentrations of inhalable and respirable dusts were measured using an aerosol spectrometer (Model 1.109; GRIMM Inc.) at the average respiratory heights of the broilers and farmers, respectively. The concentration of occupational dust was measured according to two experimental situations: when the status of the broilers was very calm ("stable" status) and when the broilers showed active and vigorous movement due to the work activity of the farmers ("active" status). Thus, the activity of broilers was defined as a nominal variable. Data were continuously recorded for 5-10 minutes and averaged.

Experimental monitoring and numerical computation of environmental variables

Air temperature and humidity were measured at seven points per each facility using thermocouples (Omega Engineering Inc., USA) and HOBO sensors (UX100-003; Onset Computer Co., USA). A portable weather station (WatchDog 2700; Spectrum Tech, Inc., USA) was installed to measure the outdoor weather condition. Every data was acquired every 1 sec. Measured wind condition data were especially useful in constructing the boundary conditions for the CFD model in order to evaluate the natural ventilation rate of the NV broiler house. The flow rates of the exhaust fans of the MV and NV broiler houses were measured using an airflow meter (our own manufactured) and a manometer (TSI-5815; TSI, USA). A portable camera (HD-3000; Microsoft, USA) was installed near the entrance door to record the status and movement

of the broilers and farmers in each broiler house. The water contents of the bedding materials were also investigated through KS F2306 test methods. To evaluate the ventilation rates of both broiler house under actual wind environmental conditions and ventilation operation strategies, CFD simulation model with TGD method was adopted.

Results and discussions

Measured concentration of inhalable at height of worker's respiratory intake

Here, we only discussed the results of the inhalable dust considering the limited length of the paper; details of results of TSP, PM10 and respirable dust will be discussed in our preparing paper. The measured results of the inhalable dust at height of worker's respiratory intake (Table 1 and 2) were typically lower than results obtained at the broiler's height in both broiler houses: 56.9-89.7% for the MV broiler house and 39.3 - 90.9% for the NV broiler house. The lower values at this height might be explained by the sedimentation rate of particulates with large AED due to the force of gravity. From the one-way ANOVA tests and their post-hoc tests, which were used to investigate the effect of seasonal changes on the inhalable dust measured, the rank of winter>autumn>summer were found for the ages of 1 (p-value = 0.047) and 2 weeks (p-value = 0.060) in the MV broiler house,. However, the order of autumn>winter>summer was found for the age of 4 weeks (p-value = 0.002). The experiment was carried out with 22-day-old broilers in the winter season, 27–day-old broilers in the autumn, and 26- and 27- day-old broilers for the summer season. Relatively small quantities of particulates can be generated from immature broilers. It can be empirically estimated that if the winter experiment was conducted with identical conditions to the other seasons, the rank of the concentration distribution might be winter>autumn>summer, as presented in previous studies. In comparison with the occupational exposure limit of inhalable dust with respect to the respiratory health of broiler farmers (Donham *et al.,* 2000), it was noted that the partially-measured concentrations of inhalable dust exceeded 2.4 mg m^{-3} during the autumn and winter seasons when a limited ventilation rate was adopted. In particular, most measured concentrations of inhalable dust exceeded the recommended level in the cold season. Excesses of 182, 108, and 143% were observed at the ages of 1, 2, and 4 weeks during the winter season in the MV broiler house, while excesses of 160 and 292% were observed at the ages of 1 and 4 weeks in the NV broiler house during identical periods.

Table 1. Mean inhalable concentrations at the average height of the worker's respiratory intake in MV and NV broiler houses (unit: mg m^{-3})

Date	**Sept-Oct 2013 (Autumn)**			**Dec 2013 (Winter)**		
Broiler's age	1 week	2 weeks	4 weeks	1 week	2 weeks	4 weeks
MV	2.360.61	1.690.14	0.60	4.370.78	2.590.32	3.420.18
NV	1.840.04	1.110.06	8.861.07	3.830.37	1.570.21	7.001.01
Date	**Jun.-Jul. 2014 (Summer)**			**Aug.-Sept. 2014 (Summer)**		
Broiler's age	1 week	2 weeks	4 weeks	1 week	2 weeks	4 weeks
MV	0.760.30	1.940.30	0.400.12	2.020.28	0.980.22	1.650.25
NV	1.200.18	1.510.06	0.480.12	1.680.40	1.880.65	1.840.48

Table 2. Mean respirable concentrations at the average height of the worker's respiratory intake in MV and NV broiler houses (unit: mg m^{-3})

Date	Sept.-Oct. 2013 (Autumn)			Dec. 2013 (Winter)		
Broiler's age	1 week	2 weeks	4 weeks	1 week	2 weeks	4 weeks
MV	0.210.04	0.150.01	0.650.04	0.510.04	0.530.07	0.630.03
NV	0.250.00	0.080.01	0.960.16	0.590.05	0.330.02	0.760.04
Date	**Jun.-Jul. 2014 (Summer)**			**Aug.-Sept. 2014 (Summer)**		
Broiler's age	1 week	2 weeks	4 weeks	1 week	2 weeks	4 weeks
MV	0.110.03	0.220.03	0.110.01	0.330.02	0.120.01	0.150.03
NV	0.150.01	0.200.00	0.160.02	0.170.02	0.170.05	0.200.05

Measured concentration of inhalable according to broiler's activity

As mentioned above, we only here discussed the results of the inhalable dust considering the limited length of the paper. Figures 4 shows example results of the inhalable dust measured in the MV broiler house according to the measurement location and activities of the broilers. When famers entered the facility, the rapid motion of flapping wings by the herd of broilers was generally observed. Consequently, the working activities of the farmers can lead to a dustier environment than what is observed in an ordinary environment. For example, when broilers were 22 days old in the MV facility during the winter season (Figure 4 (a)), the concentration of inhalable dust (mean value = 24.25 mg m^{-3}) was found to be 4.69 times higher compared to the broiler's stable status at the broiler's height; this is 655% more than the recommended level for animals. In the case of the measurement results at the worker's respiratory intake, a value that was 2.50 times higher (mean value = 9.87 mg m^{-3}) was observed. This was also 411% more than the recommended occupational exposure limit for broiler farmers.

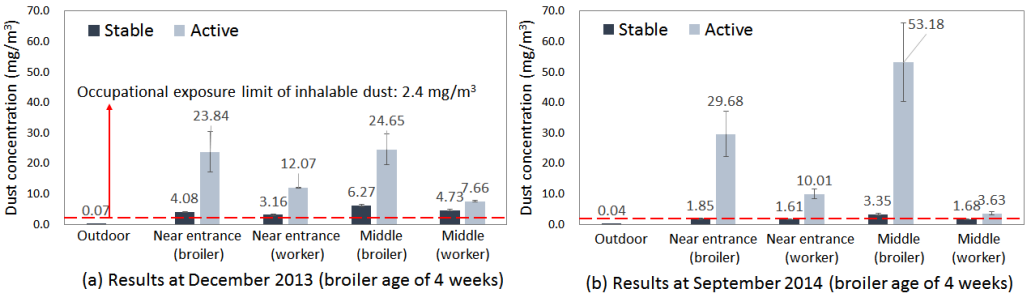

Figure 4. Results of inhalable dust measured in (a) December 2013 and (b) September 2014 in the MV broiler house according to the increased broiler activity

Identification of key factors for generation of inhalable dust

Parts of the results will be discussed considering the limited length of the paper. First, we carried out correlation analyses and multi-collinearity test then, broiler's age, CFD-computed ventilation rate, outdoor absolute humidity level, indoor air temperature, indoor absolute humidity level, water content level of the bedding materials, and activity status of the broilers(nominal factor) were finally selected as the independent variables. Table 3 shows the final results of the regression analyses for inhalable dust measured

at the heights of the worker's respiratory intake in the MV broiler house. From the multi regression analysis, the variable of the water content level of the bedding materials was excluded through the backward elimination process (p-value = 0.766). From the normality test for residuals of the regression model using the Shapiro-Wilk test, the regression model did not satisfy the prerequisite of a normal distribution (p-value = 0.003). Therefore, log-transformation was carried out. As shown in Table 3, the activity of broilers, indoor absolute humidity, and ventilation rate were found to be significant factors toward the generation of inhalable dust. This indirectly indicated that the work activities of farmers in the facility, when minimum ventilation was used in the dry and cold season, could generate high concentrations of airborne dust in the MV broiler house. If we consider that the activity status of the broilers is not a controllable factor, temporal management of the ventilation rate and humidity conditions might be helpful to reduce the dust concentration. However, increasing the ventilation rate can cause unfavorable thermal conditions in the AOZ, and increasing the indoor humidity is strongly related with the proliferation of microorganisms. Therefore, determining proper control ranges for these two variables, which consider the stability and suitability of the environmental factors, should take precedence.

Table 3. Results of multiple regression of inhalable dust measured at the worker's respiratory height in MV broiler house

Inhalable dust	Multiple R^2	0.64	Adjusted R^2	0.54
	F-statistic	6.35	p-value	0.001
	Coefficient	**Standard error**	**t-value**	**Pr (>)**
(intercept)	0.60	3.13	0.19	0.851
Age of broilers (days)	0.05	0.04	1.20	0.244
Ventilation rate (AER min^{-1})	-1.02	0.38	-2.66	0.016*
Indoor air temperature (°C)	0.07	0.10	0.72	0.481
Indoor A.H. (kg kg-da^{-1})	-156.65	49.34	-3.18	0.005**
Broiler activity*	0.87	0.24	3.68	0.002**

Significance: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1
A.H. refers to absolute humidity
* Broiler activity is a binominal factor ('0' refers to stable conditions of the broilers while '1' refers to active conditions due to the working activities).

Based on the corrected models, the linear regression equation derived for the inhalable dust at worker's respiratory height in the MV broiler house is given below.

log (Inhalable dust (worker^' s respiratory height)) = 0.595 + 0.047 · age of animals - 1.021 · ventilation rate + 0.069 · indoor air temperature - 156.645 · indoor absolute humidity + 0.873 · broiler activity

For example, based on the derived equation and experimental conditions for October 2013, where the broiler's age was 27 days, the ventilation rate was 0.07 AER min^{-1}, the air temperature was 23.67 , and the relative humidity was 74.43%, only a 1.4% decrease in the inhalable dust at the worker's respiratory height can be estimated when the ventilation rate was temporarily increased by 10% when the broiler farmers entered the facility. Meanwhile, a 13.7% decrease occurred for the case when the indoor relative humidity level was increased by 5% under identical conditions. These observations indirectly indicated that controlling the humidity level inside the facility would be more influential

than adjusting the ventilation level when considering the effectiveness of dust reduction and the effects on the thermal conditions of the AOZ due to the increase in the ventilation rate, especially in the cold season.

Conclusions

From the observations and discussions, relatively high dust concentrations were obviously measured when broiler farmers entered the facility; this was due to the increase in the broiler activity, especially in the autumn and winter seasons when a minimum ventilation rate was generally adopted. Those dust concentration values easily exceeded the occupational exposure limits per their size fractions. Based on statistical analysis, the activity of broilers was found to be a key factor for dust generation in both experimental broiler houses; however, controlling the humidity level may be a practical method to control the generation of the larger fractions, such as inhalable dust, when considering the field-applicability of each variable.

References

Al Homidan, A., Robertson, J.F., and Petchey, A.M. (2003). Review of the effect of ammonia and dust concentrations on broiler performance. *Worlds Poultry Science Journal,* 59(3): 340–349.

Banhazi, T.M., Seedorf, J., Rutley, D.L., and Pitchford, W.S. (2008). Identification of risk factors for sub-optimal housing conditions in Australian piggeries: Part 2. Airborne pollutants. *Journal of Agricultural Safety and Health,* 14(1): 21–39.

Basinas, I., Sigsgaard, T., Heederik, D., Takai, H., Omland, O., Andersen, N.T., Wouters, I.M., Bonlokke, J.H., Kromhout, H., and Schlunssen, V. (2012). Exposure to inhalable dust and endotoxin among Danish livestock farmers: results from the SUS cohort study. *Journal of Environmental Monitoring,* 14: 604–614.

Cambra-Lopez, M., Aarnink, A.J.A., Zhao, Y., Calvet, S., and Torres, A.G. (2010). Airborne particulate matter from livestock production systems: A review of an air pollution problem. *Environmental Pollution,* 158(1): 1–17.

Donham, K.J. (2010). Community and occupational health concerns in pork production: a review. *Journal of Animal Science,* 88: 102–111.

Takai, H., Pedersen, S., Johnsen, J.O., Metz, J.H.M., Koerkamp, P.W.G.G., Unek, G.H., Phillips, V.R., Holden, M.R., Sneath, R.W., Short, J.L., White, R.P., Hartung, J., Seedorf, J., Schroder, M., Linkert, K.H., Wathes, C.M. (1998). Concentrations and emissions of airborne endotoxins and microorganisms in livestock buildings in Northern Europe. *Journal of Agricultural Engineering Research,* 70(1): 59–77.

Kwon, K., Lee, I., and Ha, T. (2016). Identification of key factors for dust generation in a nursery pig house and evaluation of dust reduction efficiency using CFD technique. *Biosystems Engineering,* 151: 28–52.

Automatic broiler temperature measuring by IR camera for commercial broiler-houses

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Abstract

The continuous genetic selection for performance traits resulted in a considerable enhancement of daily feed consumption, leading to alterations in growth mechanisms and development. These developments were not accompanied by the necessary increases in the size of the cardiovascular and respiratory systems, nor sufficient enhancements of their functional efficiency. This has resulted in a relatively low capability for maintaining adequate dynamic steady-state mechanisms in the body that should balance energy expenditure under extreme environmental conditions. Thus, modern broilers have an elevated metabolic rate and consequently elevated internal heat production that leads to insufficient maintenance of dynamic steady-state of thermoregulation processes, resulting in enhancement of body temperature fluctuations.

Today in most commercial chicken houses there are temperature and humidity sensors that provide mean values of the surrounding area. However, no direct measurement is being done on the growing broiler thermal statues.

As a result, feedback mechanisms controlling the chicken-house climate might not respond according to the broilers thermal statues.

Due to that fact we have developed a prototype of a new system which measures the broiler temperature in a production house.

Keyword: broiler body temperature, invasive body temperature logger, low-cost infrared camera, commercial broiler-house sensor, features characterising body temperature

Introduction

Recent decades have seen significant development in the genetic selection of meat-type broiler chickens (Zuidhof *et al.*, 2014) for fast growth rate and high meat yield, resulting in elevated internal (metabolic) heat production (Sandercock *et al.*, 2006). However, such growth and development isn't supported by the necessary alometric increases in the size of the cardiovascular and respiratory systems (Havenstein *et al.,* 2003), leading to rather low capability to maintain adequate dynamic steady-state mechanisms in the body, that should balance energy expenditure and body water balance under extreme environmental conditions (Yahav, 2009).

Thermal stress is caused by adverse combinations of temperature, relative humidity, and air ventilation in the micro-climate surrounding the broiler. Moreover, even in temperate-climate, broiler production is negatively affected by heat, due to higher growth rate, which causes more heat generation by broilers (Sandercock *et al.*, 1995).

In order to provide the appropriate micro-climate, a modern broiler-house are equipped with insulated roof, walls and floor and with climate control system, which includes ventilation, heating, cooling and lighting. All are controlled by sensors distributed in the broiler-house space providing measurement of the environment around the broilers. As a result, broiler-house climate control system might not respond to the actual needs of

the broiler, affecting their performance and consequently reducing the broiler-house efficiency (Naas *et al.,* 2010).

Noninvasive IR technique is widely used for the body temperature (BT) estimation for animals (McCafferty *et al.*, 2015). The correlation between the broiler core BT and the outer temperature measured by an IR camera was achieved by Giloh *et al.* (Giloh *et al.,* 2012) for more than 80% of broilers in experimental broiler-house. However, all these studies used high-quality IR cameras, which is impractical for commercial applications.

The objective of this study was to develop a prototype of a new system which measures the broiler temperature in a production house. The system designed to achieve automaticity thermal images without human intervention.

Materials and methods

System design

A prototype of a broiler BT measuring system was designed and built. The prototype included a photographing space with a feed cone tray connected to a feeder line tube. The feeder had a single entrance orientated parallel to the IR camera's lens and to a RFID antenna (Figure 1).

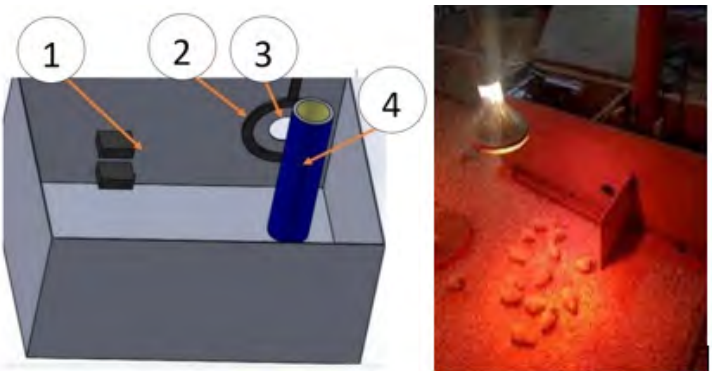

Figure 1. An early system prototype (left side) operating at the ARO's experimental broiler-house (right-side) before implementing in commercial broiler-houses. 1- Thermal cameras, 2- RFID antenna, 3- System's entrance, 4- Feeder

The IR cameras were located inside the box with appropriate distance and orientation towards the broiler head. Two types of low-cost IR cameras were tested in this experiment: FlirOne (60 × 80 pixels resolution, ±3°C accuracy) and the Lepton, (60 × 80 pixels resolution, ±5°C accuracy) both made by FLIR Systems, Inc.

Since both cameras had a temperature drift, they were calibrated by a thermistor sensor PT100 (Din 1/5) with emissivity 0.96 and located 7 cm from the cameras. The calibrating thermistor temperature was measured by a microcontroller (Uno, Arduino), calibration was calculated for each frame. The broilers were recognised by the RFID tags (APT12, BioMark Inc., USA), antenna and reader (HPR Plus, BioMark Inc., USA).

Animal experiment design:

The experiment was conducted at the ARO research experimental farm (Volcani centre, ARO). The experiment was performed on 30 male broilers (Cobb 500) chicks all implanted with RFID tags into the neck (Figure 2).

Figure 2. RFID tags were implanted in the upper side of neck

At age 14 days, 15 birds were randomly selected and implanted with temperature loggers (SL53T-A, Signatrol Ltd, UK, ±0.14°C accuracy) into the abdominal cavity. From age 14 days, onward data on feeder visiting and broiler temperature was recorded. At each feeding event, the RFID recorded the broiler number, visit time and visit duration of the head inside the cage. At each visit, the cameras captured and saved images during 20 seconds, totally 40 images (2Hz frequency).

IR images processing

The pictures were taken while broilers were moving or still. It is assumed that if the broiler was still and the image was sharp, the image represented its actual face temperature. Nevertheless, if the broiler were moving, the cameras caught a smoothed image, which was equivalent to the numerical averaging operation decreasing the maximal temperature value. Hence, among all the images with the needed head location and orientation, the image with the highest BTIR was assumed to be a sharp, and the BTIR at this image was selected as a represented BTIR during that meal. The data from the IR cameras, RFID and the temperature loggers was synchronized, comparing between the core body temperature (BTcore) monitored by the temperature loggers and body temperature (BT) predicted by a model based on images from the IR cameras (BTIR). Altogether, data about 1,220 meals was collected.

Modeling

Image features were applied in order to predict BT. Outliers temperature were filtered-out by applying moving average and median filtering. In order to calculate hot spots in the facial area an average of 3, 10, 30, 50, 100, and 300 hottest pixels for each feeding event were recorded. The temperature measured by the thermocouple and broiler age was recorded as well. A Feature Number (FN) was applied to quantify hot spots in the image. To prevent regression overestimation and to find significant features, lasso regression model with tenfold cross-validation (Hastie *et al.*, 2008) was developed. The calculations were performed on MATLAB (MathWorks 2018b).

At the validation model phase, 90% of the data were used to build the model and 10% were used for the model validation in a tenfold cross-validation technique. The advantage of this method is that all observations are used for both training and validation, and each observation is used for validation exactly once.

Results and discussion

The relation between the implanted temperature logger (BTcore) and the thermal camera (BTIR) predicted by a Lasso model for FlirOne and Lepton cameras are presented in Figure 3.

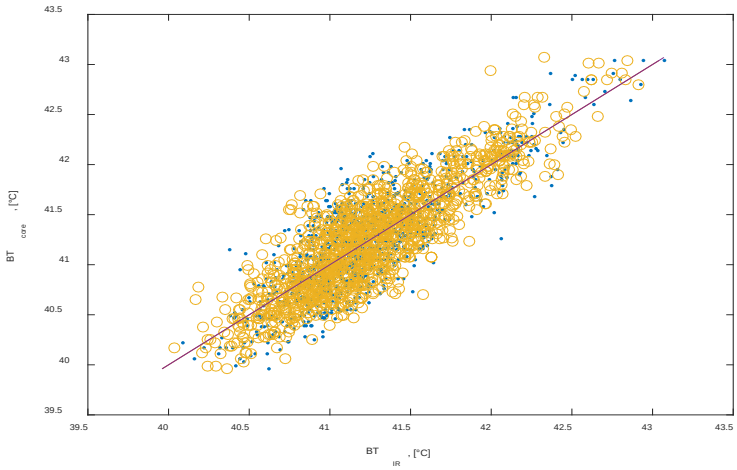

Figure 3. Camera Validation. Body temperature (BTcore) measured by implanted temperature loggers in the chicken abdominal cavity vs infrared thermography temperature (BTIR) monitored by FlirOne (dots) and Lepton (circles) cameras

Both lasso and single-dimensional regression models based on data from both cameras had presented a significant correlation with P-value < 0.001. However, R2 values calculated for the single-dimensional regression were lower compared to the ones calculated by applying the lasso regression. The highest R2 value and the minimal error between predicted BTcore and the BTIR was achieved for lasso regression and Lepton camera ($R^2 = 0.74$; Table 1).

Table 1. Model Validation. A camera based temperature vs reference body temperature (BT) measured by implanted temperature loggers in the chicken abdominal cavity

Model	Correlation [R^2]	Standard error of the estimate [°C]	Slope	Bias [°C]
Flir One – lasso regression	0.70	0.29	1.006	-0.26
Lepton – lasso regression	0.74	0.27	1.01	-0.41
Flir One – single dimensional regression	0.5	0.38	0.45	23.2
Lepton – single dimensional regression	0.57	0.35	0.56	19.6

Conclusions

In this study, we have designed and validated a new system that enables monitoring and measurement broilers BT. Data (temperature loggers as well as thermal IR images) were collected automatically, with no human interference in the monitoring process. The system applied a relatively low-cost camera. Results suggest the potential of integrating IR camera monitoring animal individual temperature into the chicken house climate control loop.

Acknowledgements

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References

Giloh, M., Shinder, D., Yahav, S. (2012). Skin surface temperature of broiler chickens is correlated to body core temperature and is indicative of their thermoregulatory status1. *Poultry Science,* 91: 175–188.

Havenstein, G.B., Ferket, P.R., Qureshi, M.A. (2003). Carcass composition and yield of 1957 versus 2001 broilers when fed representative 1957 and 2001 broiler diets. *Poultry Science*, 82: 1509–1518.

McCafferty, D.J., Gallon, S., Nord, A. (2015). Challenges of measuring body temperatures of free-ranging birds and mammals. *Animal Biotelemetry*, 3: 33.

Naas, I.D., Romanini, C.E.B., Neves, D.P., do Nascimento, G.R., Vercellino, R.D. (2010). Broiler surface temperature distribution of 42 day old chickens. *Sci Agr,* 67: 497–502.

Sandercock, D.A., Hunter, R.R., Mitchell, M.A., Hocking, P.M. (2006). Thermoregulatory capacity and muscle membrane integrity are compromised in broilers compared with layers at the same age or body weight. *Br Poult Sci.,* 47: 322–329.

Sandercock, D.A., Mitchell, M.A., MacLeod, M.G. (1995). Metabolic heat production in fast and slow growing broiler chickens during acute heat stress., Br. Poult. Sci., p. pg. 868

Yahav, S. (2009). Alleviating heat stress in domestic fowl - different strategies. *World Poult. Sci. J.,* 65: 719–732.

Zuidhof, M.J., Schneider, B.L., Carney, V.L., Korver, D.R., Robinson, F.E. (2014). Growth, efficiency, and yield of commercial broilers from 1957, 1978, and 2005. *Poultry Science*, 93: 2970–2982.

Individuality of laying hens within large groups and the relationship with temporal space usage

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Abstract

Consistent individual variation in animal behaviour has been identified as a major source of between-animal variability, affecting activity, immune responses, and health status. Despite these insights, laying hens are usually observed at the group-level with little consideration to individual differences in behaviour and their consequences. In a large-scale explorative study, the movement and location patterns of laying hens in a semi-commercial system was recorded by means of a RFID tracking system within four different areas (indoor, exterior winter-garden, yard and free range areas). Our methods allowed for characterisations of spatio-temporal patterns based on movements between areas as well as identifying non-random social associations based on co-occurrence at specific sites. We found that the laying hens developed a pronounced social network of differentiated individual associations that linked with spatio-temporal activity patterns. To characterise hens based on the level of similarity of ranging patterns, dissimilarity matrices were generated by Dynamic Time Warping. Cluster analysis suggests a small set of 4 - 5 distinct activity patterns with ranging patterns that were consistent over time and varied more between hens than within hens. Interestingly, similarity in daily activity patterns was highly correlated with social associations and closely associated birds became more similar with increasing age. To our knowledge, this is the first study linking animals' social niches with temporal activity patterns. The observed patterns and novel relationships identified revealed exciting opportunities to understand the complex behaviours of commercial laying hens and the observed variation in animal health, welfare, and productivity.

Keywords: laying hen, range use, social structure, RFID

Introduction

Most livestock species, including poultry, are understood to have social networks and consistent behavioural tendencies across time, though the vast majority of research has been performed using small groups of animals e.g. less than 20. While these conditions may be relevant for poultry within natural settings or small flocks where social groups are typically between 20–40 animals, the group sizes of commercial poultry within modern non-cage systems can range between one and 80,000. In particular, laying hens in small groups (e.g. less than 100 animals) can retain the identities of conspecifics (Guhl, 1953) and will have a relatively rigid hierarchical social structure (Guhl, 1953; Craig *et al.,* 1969; Dawkins, 1995; D'eath & Stone, 1999). As the size of the group increases, it becomes increasingly difficult for hens to recognise and retain the identity of conspecifics and their position in the hierarchy. In turn, hens will adopt an alternative social structure where less overall aggression is seen with certain hens adopting defensive postures for certain key resources e.g. initial access to the feeder when fresh feed is provided (reviewed by Croney and Newberry, 2007). Given the scale of resources (e.g. outdoor access and multi-tier aviaries) that laying hens are often provided, it is important to understand how hens use and interact with these environments to ensure health, welfare and productivity are optimised.

Although other livestock species (e.g. cattle, swine) have made dramatic advances in the area of Precision Livestock Farming, laying hens have unique conditions including relatively smaller body size and higher stocking densities which require novel approaches. Our group has been developing tracking technology, protocols and statistical methods in order to assess the behavioural dynamics of these large commercial poultry flocks. The current manuscript is a continuation of our initial effort to apply novel behavioural metrics (Rufener *et al.,* 2018) to assess social networks over 25 weeks within a commercial flock.

Methods

Our study utilised four side-by-side pens within a commercial barn. A pen contained 355 Brown Nick laying hens and three connected outside areas: a winter-garden, stone yard, and a grass-covered pasture area. Each pen area was outfitted with radio frequency identification antennae that allowed tracking of animals within the three outside areas and, by default, the house interior. When the barn was populated (18 weeks of age), 110 hens from each pen (i.e. approximately 1/3) were selected in a standardised manner and given a transponder, which, when in proximity to the antennae, registered that animal's presence. Each focal animal's location within the key areas, including the time and date of movement between two areas, was recorded by the system and stored on a dedicated computer. Approximately 120 days of data were collected with all irregular events (e.g. vaccinations) that occurred being written in a barn journal by the producer. Due to a combination of factors including poor weather and behavioural testing as part of a related project, hens were provided access to all areas on only 72 days of the observation period. Hens were given access to the winter garden on all days per company policy.

To characterise hens based on the level of similarity of ranging patterns, dissimilarity matrices were generated by Dynamic Time Warping using the 72 days of collected data and cluster analysis applied to determine groups of hens with consistent movement patterns. To assess social network cohesion, for each transition of a hen between two areas, we identified all other hens that performed the same transition within five seconds and generated a daily grouping metric for each hen. We then assessed the stability of that grouping over the duration of the study.

Results and discussion

Our methods allowed for characterisations of spatio-temporal patterns based on movements between areas as well as identifying non-random social associations based on co-occurrence at specific sites. Examination of Dynamic Time Warping pairwise comparisons for variation within hens versus all other hens across time found within hen variation to be consistently lower, suggesting hens were more similar to themselves across time than to other hens (Figure 1). In other words, accounting for hen individuality is a critical source of behavioural variation as individual hens appeared to maintain time-dependent movement patterns despite flock-level changes over time which likely resulted from age-dependent changes and shared external factors e.g. disturbances.

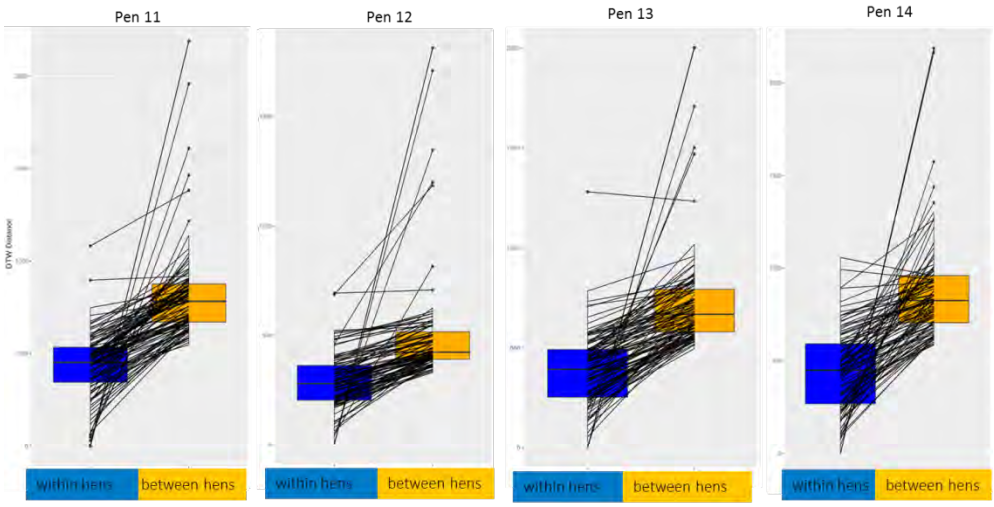

Figure 1. For each pen, the raw Dynamic Time Warping distances of pairwise comparisons are smaller for within hen comparison (blue, each hen compared to its own) than between hen comparisons (yellow, hen x compared to all other hens across time)

The daily means of all pairwise Dynamic Time Warping distances of all hens for each day manifested a clear downward trend over time despite some obvious outlier days (Figure 2). Typically, these large outliers were associated with a management protocol that restricted access to one of the locations for a period of time.

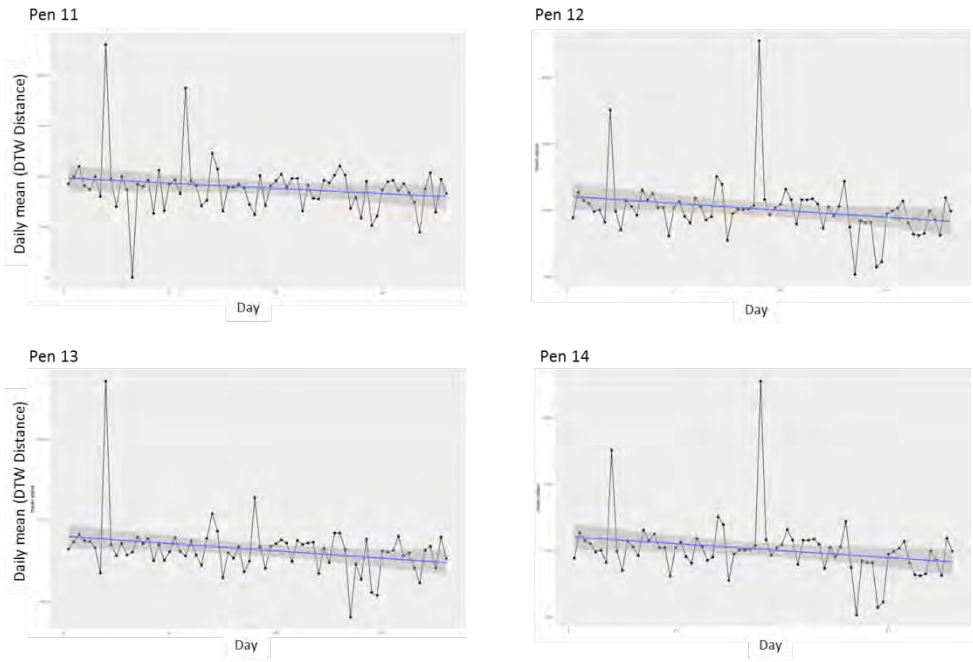

Figure 2. Daily mean of all pairwise Dynamic Time Warping distances of all hens for each day

We also found that laying hens developed a pronounced social network of differentiated individual associations that linked with spatio-temporal activity patterns. Interestingly, similarity in daily activity patterns was highly correlated with social associations and closely associated birds became more similar with increasing age.

Conclusions

To our knowledge, this is the first study linking animals' social niches with temporal activity patterns. The observed patterns and novel relationships identified revealed exciting opportunities to understand the complex behaviours of commercial laying hens and the observed variation in animal health, welfare and productivity.

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References

Craig, J.V., D.K. Biswas, and A.M. Guhl. (1969). Agonistic behaviour influenced by strangeness, crowding and heredity in female domestic fowl (Gallus gallus). *Animal Behaviour,* 17: 498–506.

Croney, C.C., and R.C. Newberry. (2007). Group size and cognitive processes. *Applied Animal Behavioural Science,* 103: 215–228.

D'eath, R.B., and R.J. Stone. (1999). Chickens use visual cues in social discrimination: an experiment with coloured lighting. *Applied Animal Behavioural Science*, 62, 233–242.

Dawkins, M.S. (1995). How do hens view other hens? The use of lateral and binocular visual fields in social recognition. *Behaviour,* 132: 591–606.

Guhl, A.M. (1953). Social behavior of the domestic fowl.

Rufener, C., J. Berezowski, F. Maximiano Sousa, Y. Abreu, L. Asher, and M.J. Toscano. (2018). Finding hens in a haystack: Consistency of movement patterns within and across individual laying hens maintained in large groups. Scientific Reports, 8: 12303.

Real-Time Locating System to study the persistence of sociality in large-mammal group dynamics

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Abstract

Many animals live in highly structured groups. Individual differences in the number and identity of social contacts define the social network structure. Most domesticated animals belong to such species. The composition of groups can be disturbed by grouping animals according to age or production stage, which can in turn induce stress. We investigated whether the preference of two animals to stay together depends on their sociality or on the composition of the group. We observed 158 dairy cows in six pens during 17 weeks. The precise positions of the cows were monitored with positional loggers 24/7 in stable groups and during the formation of new groups. In stable groups, the sociality of a cow was maintained over the entire observation period. When introducing foreign individuals into well-established social groups, the sociality of individual cows was maintained independently of the group; this sociality was therefore not necessarily defined by the time spent in the group. During the formation of new groups, newly introduced cows dynamically interacted with resident ones, forming a few strong short-lasting contacts between newcomers and resident cows. However, most long-lasting interactions occurred between resident group members. Our study reveals that in a species that spontaneously lives in large social groups, such as cattle, each animal has its own sociality independent of group. However, when it comes to establishing strong relationships between newcomers and resident animals, more than two weeks is needed.

Keywords: Precision Livestock Farming, RTLS, animal behaviour, social network, cattle

Introduction

Many animals are gregarious. Within a group, animals vary in their readiness to interact with others and their affinities to specific partners. Such a complexity can be represented by social networks where the individuals and the whole group can be characterised by a number of statistics (Krause *et al.*, 2007; Wey *et al.*, 2008). For instance, an individual can be characterised by the number of its immediate neighbours, the strength of its relations with these neighbours, the number of individuals its neighbours are connected to (clustering coefficient), and so on. Such statistics can also be calculated at group level to characterise the network as such. The structure of social networks is likely to have high impact on fitness, both impacting on cooperation between animals, information transfer, reproductive success of specific individuals, and also disease transmission (Krause *et al.*, 2007; Wey *et al.*, 2008).

Domesticated animals mostly belong to gregarious species that spontaneously live in structured groups. Cattle represent a common type of large domesticated animals with a high sociality. Groups of cows are formed thanks to dominance/subordination relationships and to preferential relationships (Reinhardt & Reinhardt, 1981; Bouissou *et al.*, 2001; Stoye *et al.*, 2012). When two cows are mixed together for the first time, they exchange aggressive interactions (fights, butts), but once the dominance/subordination

relationship is established (i.e. only one gives butts to the other, but not vice-versa) then the frequency of aggressions declines dramatically and the hierarchy remains stable (Bouissou *et al.*, 2001). Preferential relationships are also observed, whereby animals stay close to each other, synchronize their activities (e.g. eating, walking, resting), and exchange mild interactions such as sniffing and allo-grooming (Gibbons *et al.*, 2010).

Under farm conditions, the groups are shaped by humans and animals can be moved from one group to another according to their sex, age or production stage (e.g. cows in milk vs dry cows), no matter their social preferences. Previous studies showed that mixing animals can be stressful, inducing a dysregulation of the corticotropic axis and a decrease in growth or milk production (Hasegawa *et al.*, 1997; Mounier *et al.*, 2005). This is likely to be due to aggressive interactions between animals that do not know each other. In addition, the social buffering properties of the group – by which animal stress is reduced by the presence of group mates – is diminished (Mounier *et al.*, 2006). We suspect that such effects of mixing animals result from the whole social network being disturbed.

We used a Real Time Locating System (RTLS) to record the position of each individual cow housed in a free stall at every second 24/7 for 17 weeks. The underlying assumption is that cows spending time together interact socially. Using these high-resolution data, we were able to build dynamic interacting networks between cows. We analysed the sociality of cows in stable group, then we followed the introduction and removal of individuals between groups. We focus our study on two levels of sociality persistence: in an individual moving from one social group to another, and in a group experiencing the introduction of many newcomers.

Material and methods

The observations were performed at the INRA Herbipole farm (UE1414, France). There were on average 158 cows in the barn per week, 75% Holstein and 25% Montbeliard cows. They were housed in six pens with a maximum of 28 cows per pen. Each pen consists of a feeding area on one side and two rows of 14 cubicles (1.25 m × 2.53 m) on the other side (Figure 1).

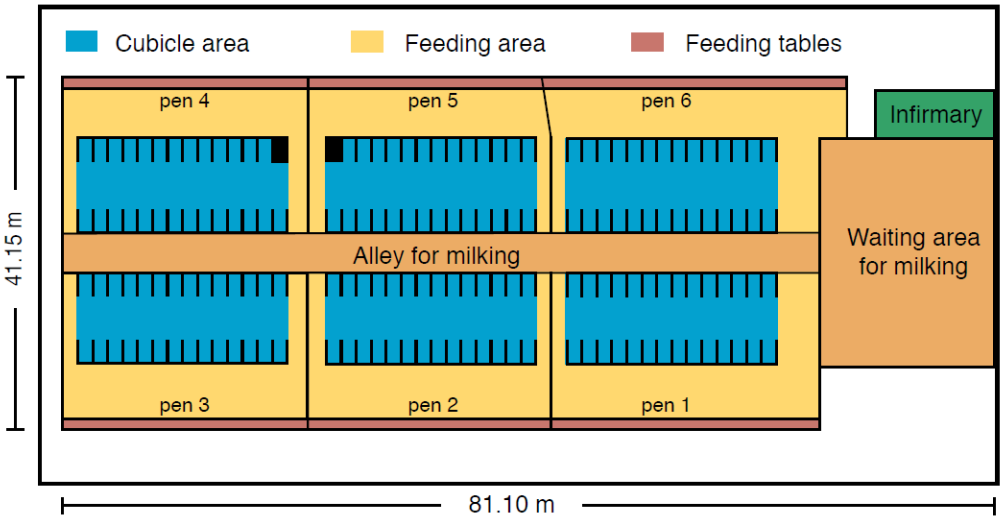

Figure 1. Barn composed of six pens, each with a capacity of accommodating 28 cows

All observations were done under the routine management of the farm. We first observed the dynamics of two stable groups of cows in Pen 4 (18 cows) and Pen 5 (17 cows). The cows knew each other for at least one year, except five heifers in each pen that had been introduced one month before the observations. Both groups remained stable throughout the 17 weeks of observation, except that a cow was introduced in Pen 4 on Week 13 and another removed on Week 15. Then we observed unstable groups, with cows moved from Pens two or three to Pen 1. Finally, we analysed how the social network changes in a specific Pen 2 when, after a period of three weeks of stability, nine cows were removed and eight cows (from different pens) were moved in. This pen was observed from one week before, to two weeks after, this reshuffling.

We recorded the position of the cows with the CowView system (GEA, Germany). Each cow was equipped with a tag on its neck collar. Every second, the tag emits radio waves within the ultra-wideband area, which are detected by antennae within the barn. The accuracy of the position is on average 50 cm in the whole barn. We applied a rolling median filter of three consecutive positions to remove outliers and minimise the noise. Because of missing data, due e.g. to physical blockage of the signal from time to time, we focused on cows that were detected for at least 2/3 of a day (i.e. 16 h) for at least 2/3 of the total time (i.e. 80 days). This resulted in the collection of data for 158 cows out of the 188 that stayed in the barn.

We considered that two cows were in contact with each other when the distance between their tags was 1.25 m or less for at least 10 minutes of a day when they were outside the cubicle area. We defined the sociality of a cow during a given day as the number of other cows she was in contact with. We also calculated the average sociality of a cow over a week. To study social networks, we looked at all dyadic contacts of cows within a pen, measuring the total time two cows have been close to each other; in this case we used a threshold of 25 minutes to consider that cows were in contact with each other.

Results

The sociality of cows varies within a group. In Pens 4 and 5 that were stable along the observations, some cows contacted up to 14 other cows during a single day whereas other cows contacted one or even no partner. This characteristic seems stable across days. We divided artificially cows from each pen in three equal groups according to their sociality across the 17 weeks of observations: high vs moderate vs low sociality. In each pen, the three groups were statistically different along the 17 weeks: respectively for high, moderate, and low sociality cows, 5.89 ± 0.44, 4.35 ± 0.34 and 1.85 ± 0.60 contacts per day in Pen 4 ($F = 127.1$, $P < 0.0001$) and 3.67 ± 0.34, 2.94 ± 0.23, and 2.19 ± 0.44 contacts in Pen 5 ($F = 25.14$, $P < 0.0001$), with binary differences between groups also significant ($P < 0.01$).

Five cows were introduced in Pen 1 on Day 18, one from Pen 2 and four from Pen 3. These cows remained in the same sociality class (relative to the pen) from before to after introduction in Pen 1, suggesting that sociality is a trait that depends essentially on the individual and not the group.

When Pen 2 was reshuffled, the average duration of contacts between resident cows did not change significantly (from 106 ± 29.8 s on the week before the reshuffling, to 94.5 ± 28.4 s one week later and 74.5 ± 29.3 s the week after, $P > 0.05$). However, these contacts were not necessarily between the same cows (no correlation between dyadic contacts before and two weeks after the reshuffling). After their introduction, the new cows had strong contacts with the resident cows; however, with whom the contacts were established changed from one day to another. As a consequence, when averaged over a week, the dyadic contacts between resident and newcomer cows were still scarce two weeks after

the replacement (Figure 2). At the same time, the strength of the social network within the pen deceased: on average 2,400 s of contacts between pairs of cows before the reshuffling to 2,080 s during the first week after reshuffling and 1,750 s the week after.

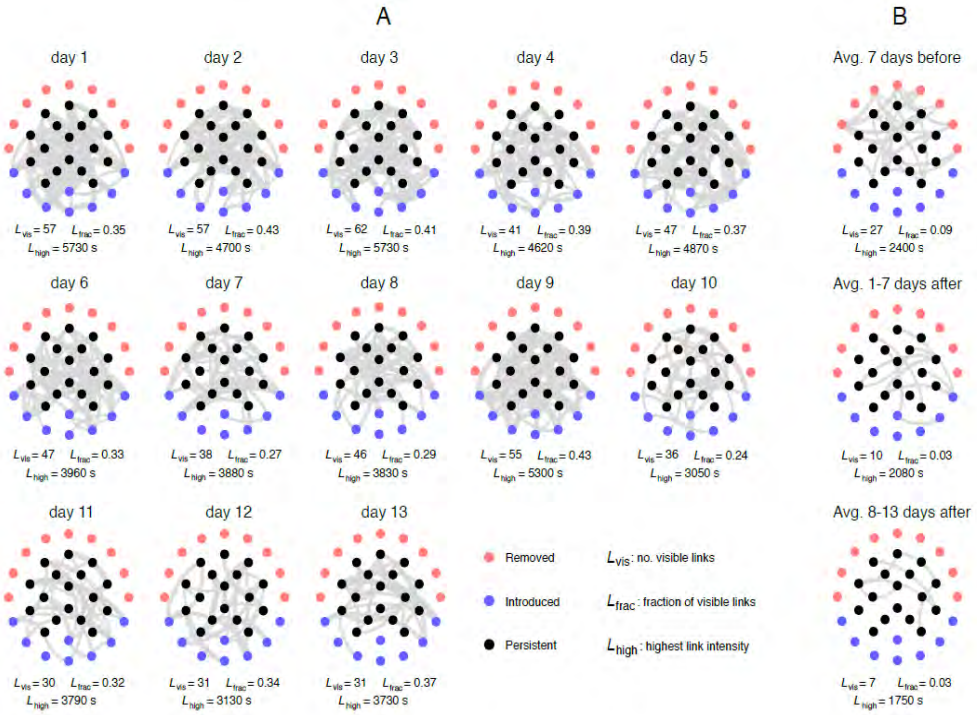

Figure 2. Network within Pen 2 before and after the replacement of nine resident cows by eight newcomers. L_{vis}, contacts between animals that lasted 25 min/d or more; L_{frac}, proportion of L_{vis} over all contacts whatever their duration; L_{high}, the longest duration of contact between two cows

Conclusion

With a simple RTLS device we were able to characterise cows according to their sociality, that is their readiness to get close to – and probably interact with – other cows from their group. This characteristic seems stable over time, at least for the 17 weeks of observation of our study, and to depend more on the individual than the group it is in.

Groups of cows also seem to form a whole entity characterised by a network defined by dyadic connections between cows. This network is disturbed when cows are replaced by newcomer cows: not only does it take more than two weeks for the newcomers to mix with the resident cows, but also the network between the former resident cows is weakened.

RTLS can be used to study the social behaviour of cattle. It can also be used to monitor disturbances due to mixing, such mixings occurring frequently in farming. The cohesion of social groups is essential to encourage cooperation between animals and reduce stress (see introduction). RTLS could be used by farmers to ensure the proper functioning of groups of animals, identifying animals which have difficulties to get in contact with others and whose welfare is likely at risk or identifying groups where the social cohesion is poor. It could thus help the management of social groups by farmers.

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References

Bouissou, M.F., Boissy, A., Le Neindre, P., Veissier, I. (2001). The social behaviour of cattle, in: L.J. Keeling (Editeur), H.G.E. (Ed.), Social behaviour in farm animals, CABI Publishing, GBR, pp. 113–144.

Gibbons, J.M., Lawrence, A.B., Haskell, M.J. (2010). Measuring sociability in dairy cows. *Appl. Anim. Behav. Sci.,* 122: 84–91.

Hasegawa, N., Nishiwaki, A., Suguwara, K., Ito, I. (1997). The effects of social exchange between two groups of lactating primiparous heifers on milk production, dominance order, behavior and adrenocortical response. *Appl. Anim. Behav. Sci.,* 51: 15–27.

Krause, J., Croft, D.P., James, R. (2007). Social network theory in the behavioural sciences: potential applications. *Behavioral Ecology and Sociobiology,* 62: 15–27.

Mounier, L., Veissier, I., Andanson, S., Delval, E., Boissy, A. (2006). Mixing at the beginning of fattening moderates social buffering in beef bulls. *Appl. Anim. Behav. Sci.*, 96: 185–200.

Mounier, L., Veissier, I., Boissy, A. (2005). Behavior, physiology, and performance of bulls mixed at the onset of finishing to form uniform body weight groups. *J. Anim. Sci.,* 83: 1696–1704.

Reinhardt, V., Reinhardt, A. (1981). Cohesive relationships in a cattle herd (Bos indicus). *Behaviour,* 77: 121–151.

Stoye, S., Porter, M.A., Stamp Dawkins, M. (2012). Synchronized lying in cattle in relation to time of day. *Livestock Science,* 149: 70–73.

Wey, T., Blumstein, D.T., Shen, W., Jordan, F. (2008). Social network analysis of animal behaviour: a promising tool for the study of sociality. *Anim. Behav.* 75: 333–344.

Developing an automatic system aiming to detect and deter migrating birds from aquaculture ponds

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Abstract

Israel is a major global migration route for many species of fish-eating birds, such as pelicans and cormorants. This migration carries high costs for aquaculture in fish predation and the spread of disease in the fish ponds. The aim of this study was to develop a computerised automatic system to detect and deter fish-eating birds from fish ponds.

We developed a system that detects pelicans and sends a small boat to deter them. The system comprises a radio-controlled boat (1 m long), a stationary video camera, a computer, and a detection algorithm. The camera (Dahua camera, DH-IPC-HFW4830E-S) was connected to the computer via an Ethernet cable to collect video sequences of a focal pond. The detection algorithm is based on a convolutional neural network, and classifies different regions as containing pelicans, or not. Data were recorded over the three months before the migration season. The data contained videos of between two and 50 pelicans per video. The size of the test fish pond was 10^5 m^2 with a maximum range of 600 m to the pelicans as they floated.

The detection complexity varies according to air clarity, cloud cover, and target proximity. Pelicans were detected on clear days, cloudy days, and with different distances to the camera. The detection accuracy was 98%. The accuracy was calculated based on a dataset that was built for this project. The system is currently being tested and is on the way to become fully automatic.

Keywords: fish farming, birds detection, birds deterrence, deep learning, ResNet, automated birds deterrence

Introduction

Migrating fish-eating birds are giving the aquaculture industry a hard time, as they stop at fish ponds during migration, and eat many fish. This has become a worldwide problem (Stickley & Andrews, 1989). The cost of this phenomenon in the Spring Valley of Israel is approximately 3M shekels per year. The cost comprises the fish that were consumed by the birds and the efforts made by the deterrence teams. These teams are trying to deter the birds in multiple ways such as: driving fast trucks along the pond, scaring the birds with loud noises such as horns, shooting dummy bullets in the air, and at night using bright flashlights and lasers.

None of the above methods are quite successful, as the birds get accustomed to these disturbances. However, as the birds become more exhausted and hungrier, they are more willing to take risks in spite of the deterrence efforts. This factor further reduces the ability of the teams to deter the birds.

The best deterrence method at present is to send a boat towards them. As the boat approaches, the birds fly away to avoid a collision. It is a challenge to deter hungry birds, but a fast boat that heads towards them will manage to deter them nevertheless. The birds don't get accustomed to the boat, because every time it comes from a different direction.

In this work a system was developed that detects and deters birds by sending a boat towards them. The spatial detection is done with a deep learning classifier, while the exact location of the birds isn't crucial as the birds fly away when the boat is approx. 15 meters from them.

Materials and methods

Data collection

The data collection was done with a camera installed in a test fish pond, in the north of Israel. The camera was connected to a computer, constantly imaging the pond. The exact time when the pelicans and cormorants landed in the pond was documented. The videos were later analysed, and long videos were cut to shorter videos of about 40 minutes each, containing the birds swimming in the water. The next stage of the process was saving images every 10 seconds, to create a dataset of different images. In this process a dataset of 990 images of 2,380 × 180 pixels was made, containing images of the birds swimming in the water in different lighting conditions, and at different times of the day. A sample image is presented in Figure 1.

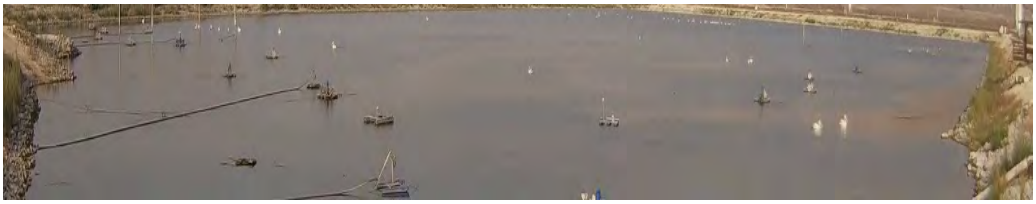

Figure 1. An image taken from the test fish pond

Birds detection and data labeling

In order to detect birds in the pond, every image was divided into 40 by 40 pixel sections, then every section was labeled into class 1 or 0; class 1 meaning a section with birds and class 2 a section without birds.

This sectioning and labeling was performed for all of the 990 images mentioned above with PYTHON code that was written especially for this task. A section was labeled class 1 if there were any birds appearing in it.

Birds may appear differently, depending on their distance from the camera and orientation; Figure 2(d)-(f) contains birds. They may appear as small white colour stains for instance Figure 2(d), or as a white homogenous area Figure 2(e), or as actual birds Figure 2(f).

Images without birds may contain objects like floaters Figure 2(a) and (b), or may contain no objects at all, Figure 2(c).

Images (c) and (d) in Figure 2 are very alike, other than the two pelicans appearing as little white stains. Images (a) and (f) in Figure 2 resemble each other, even though they belong to different classes.

a b c d e f

Figure 2. 40 × 40 sections; (a) - (c) are sections without birds; (d) - (f) are sections containing birds

In the labeling process 22K labeled 40 × 40 pixel sections were made, 11K for each class.

Classification algorithm

A well-trained deep learning classifier requires a lot of training images. Thus the 22K labeled dataset was divided into 15,400 training images, 3,300 validation images, and 3,300 test images. The classifier was then trained with the training set, while using the validation set to inspect the training process, making sure the network was converging. The classifier was based on ResNet architecture (He *et al.*, 2016), and contained residual blocks to extract features from the images.

The system

As mentioned, the system comprised a boat, a camera, and a detection algorithm. The boat worked with ARDUPILOT software and a PIXHAWK processor that was controlled via PYTHON scripts. The system detected the birds, and sent the boat to deter them.

A classified image can be seen in Figure 3, where the birds are surrounded with green squares, which are the small sections classified as class 1.

Figure 3. Detected birds in the test fish pond, in two different images

Results and discussion

The classifier was trained on the train set, and obtained 98% accuracy on the test set.

It classified the test images in different lighting conditions and with different distances of the birds from the camera. The classifier didn't classify the floaters as pelicans, even though they might have somewhat similar features as the birds. Figure 3 represents two examples of classified images, where the sections classified as birds are marked in green.

Conclusions

Birds can be detected in the images from the test fish pond, with good accuracy. The birds can be detected at different distances from the camera, up to 600 m. The classifier was robust to scene changes, such as different lighting conditions and varying numbers of birds. Thus, it can be used for the deterrence system.

With further training the accuracy may be increased, so the system will detect birds in different fish ponds, without additional training of the classifier.

References

Draulans, D. (1987). The effectiveness of attempts to reduce predation by fish-eating birds: a review. *Biological Conservation*, 41: 219–232.

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In: *The IEEE Conference on Computer Vision and Pattern Recognition*. The 29th IEEE Conference on Computer Vision and Pattern Recognition., IEEE, Piscataway, NJ, pp. 770–778.

Littauer, G.A., Glahn, J.F., Reinhold, D.S., & Brunson, M.W. (1997). Control of bird predation at aquaculture facilities: Strategies and cost estimates. *Southern Regional Aquaculture Center Publication*, *401*.

Price, R.R., Hall, S.G., & Allen, D.G. (2006). *U.S. Patent No. 7,052,348*. Washington, DC: U.S. Patent and Trademark Office.

Stickley, A.R., & Andrews, K.J. (1989). Survey of Mississippi catfish farmers on means, effort, and costs to repel fish-eating birds from ponds. In: Craven S.R. *Eastern Wildlife Damage Control Conferences*. The Fourth Eastern Wildlife Damage Control Conference, p. 39.

Assessing individual activity levels in two broiler lines using an ultra-wideband tracking system

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Abstract

Individual data on activity of broilers is valuable for breeding programmes, as activity may serve as proxy for multiple health, welfare and performance indicators. However, in current husbandry systems, broilers are often kept in large groups, which makes it difficult to identify and monitor them at the individual level. Sensor technologies, such as ultra-wideband (UWB) tracking systems, might offer solutions. This paper investigated the recorded distances of an UWB tracking system that was applied to broilers, as a first step in assessing the potential of an UWB tracking system for studying individual levels of activity in broilers housed in groups. To this end, the distances moved as recorded by the UWB system were compared to distances recorded on video, using Kinovea video tracking software. There was a moderately strong positive correlation between the output of the UWB system and video tracking, although some under- and over- estimations were observed. Even though the recorded distances from the UWB system may not completely match the true distances moved, the UWB system appears to be well-suited for studying differences in activity between individual broilers when measured with the same system settings.

Keywords: tracking, broilers, activity, ultra-wideband

Introduction

Animals are kept in large groups in husbandry systems, which makes it difficult to identify and monitor individual animals. Still, there is an interest in quantifying individual behaviours of group-housed animals to study the link between individual behaviour and performance in more detail. Broilers are an example of a livestock species for which data on individual behaviour could prove to be valuable. Commercial selection of broilers has resulted in fast growth (Zuidhof *et al.*, 2014). At the same time, broilers may show different activity levels. For example, Weeks *et al.* (2000) found that broilers between 39–49 days of age spent on average 76 - 86% of the time lying, depending on whether the birds were sound or showed varying degrees of lameness. Additionally, with increasing age of broilers, decreases in activity are seen (e.g. Weeks *et al.*, 2000; Tickle *et al.*, 2018). The relationship between individual level of activity and leg health, welfare and performance is valuable for broiler breeders. This requires detailed information on activity of individual broilers. Sensor technologies may aid in obtaining this information. In this study, an ultra-wideband (UWB) tracking system was implemented and its suitability for individual tracking of broiler activity was investigated. The main objective was to validate the recorded distances moved of the UWB system, by comparing these to distances recorded on video, where it was assumed that the distances recorded on video were the true distances moved by the broilers.

Material and methods

Population

Data were collected at a broiler farm, under control of Cobb Europe. In total, 24 male broilers from two genetic crosses were housed in a pen with a size of 6.4 m^2 with feed and water provided ad libitum. These birds were taken from a larger group, selecting the lowest and highest body weights. From each cross, three heavyweight and three lightweight birds were selected for UWB tracking. The average weight of the light birds was 0.42 kg, while the heavy birds weighed on average 0.63 kg, as measured on day 15 of life. These six broilers per cross were fitted with an UWB tag and were tracked with the UWB system.

Ultra-wideband tracking system

A Ubisense UWB system with Series 7,000 sensors and compact tags (Ubisense Limited, Chesterton, United Kingdom) was used, in combination with TrackLab software (Noldus Information Technology, Wageningen, the Netherlands). Broilers were fitted with a Ubisense tag with a size of around 3.5 × 3.5 cm and a weight of around 25 grams on their backs, using elastic bands around their wing base. Every 6.91 seconds, these tags sent out a signal. Four Ubisense beacons, which could receive these signals, were placed in a square above the broilers' pen. Using the time of arrival of the signal, the location of the tags could be determined. The 12 broilers were tracked from day 15 to day 33 of life (n = 19 days), for approximately one hour each day, at different times. This one-hour sample per day was deemed sufficient as the main interest here was validating UWB recordings and not studying individual activity patterns over time. The resulting UWB output used in this study was the total distance moved in meters per individual per tracking session.

Video analysis

Video recordings were made from above the pen, at the same time as the UWB recordings were made. A Zavio B6210 2MP (Zavio Inc., Hsinchu City, Taiwan) video camera was used and the recordings were analysed using Kinovea video analysis software version 0.8.25 (http://www.kinovea.org/). Using Kinovea, individual broilers could be tracked throughout the pen to assess the moving distance. The length of one side of the octagonal pen was used for calibration. Manual corrections were applied when necessary, for example, when the bird was flapping its wings or was very close to other birds. The output used here was the total distance moved in meters per individual per session.

Statistical analysis

For one bird, no data were available for day 29–33, resulting in a total of 223 samples of recorded distances from both the UWB system and video tracking. Statistics were performed using R version 3.5.2 (R Core Team, 2018). The correlation between the distance moved, per individual and per session, as recorded with the UWB system and using video tracking was studied using a repeated measures correlation (package rmcorr; Bakdash & Marusich, 2018) and a Pearson correlation. The level of statistical significance was set at 0.05. Reported results are rounded to two decimals.

Results and discussion

The data were not normally distributed. However, when comparing square root-transformed data and untransformed data, the results were very similar. Therefore, the untransformed data and results are presented here. The repeated measures correlation was used to correct for the repeated measures on the same individuals and tags. However, the results of the Pearson and repeated measures correlation were virtually the same, so only the results of the Pearson correlation are reported here. A moderately strong positive correlation between video tracking and UWB tracking was found (Pearson correlation, r

= 0.71 (95%-CI: 0.64-0.77), df = 221, $P < 0.001$; Figure 1). This correlation indicates that the UWB system can provide reliable information on distances moved by broilers. However, it does appear that when broilers move less, the distance moved according to the UWB system is generally an overestimation of the distance determined by video analysis (Figure 1). Furthermore, it appears that the UWB system underestimates the distance moved when broilers move more (Figure 1). This may be the result of the implemented sampling rate of 6.91 seconds. With each sample that is received, there can be some noise, i.e. the triangulation-based location of the tag may deviate slightly from the actual location. Consequently, if an animal moves very little, this noise can make up a relatively large part of the total registered distance, which could explain the overestimation by the UWB system. Alternatively, if an animal is very active, some of the movement of the animal between samples might be missed by the system. However, a previous study in which different sampling rates were compared for agreement between distances moved with the UWB system and on video indicated that the sampling rate used in the current study was the best fit for the current implementation (personal communication Hijink, 2018).

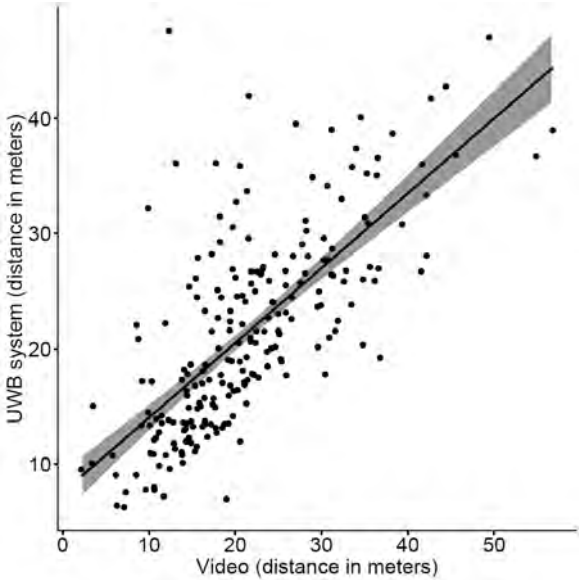

Figure 1. Plot of the correlation between the distances found with the UWB system and the distances found in video observations using Kinovea. The grey area represents the 95% confidence interval of the correlation

It is currently being investigated whether the UWB system is capable of detecting differences in level of activity over time between individual broilers of four crosses and of different weights. Preliminary results indicate that the UWB system can detect decreases in activity over time and that birds with a lower weight at about 14 days of age are on average more active than heavier birds, but further analysis is required to confirm these findings.

Conclusions

This paper showed the first step in investigating the potential of an UWB tracking system to study individual levels of activity in broilers. The main focus was on validation of the distances recorded by the UWB system. There was a moderately strong positive correlation between the recorded distances from the UWB system and from video. Although the

distances that are recorded with the UWB system may not fully match the distance moved in reality, likely due to the implemented sampling rate, the UWB system appears to be well-suited for studying activity differences between individual broilers when measured with the same system settings. Longitudinal information on activity can provide insight into what the activity levels of individuals can indicate about leg health, welfare and performance, but further research into this relationship is required.

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References

Bakdash, J.Z., and Marusich, L.R. (2018). rmcorr: Repeated Measures Correlation. R package version 0.3.0. URL: https://CRAN.R-project.org/package=rmcorr.

R Core Team. (2018). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL: https://www.R-project.org/.

Tickle, P.G., Hutchinson, J.R., and Codd, J.R. (2018). Energy allocation and behaviour in the growing broiler chicken. *Scientific Reports*, 8, article number 4562.

Weeks, C.A., Danbury, T.D., Davies, H.C., Hunt, P., and Kestin, S.C. (2000). The behaviour of broiler chickens and its modification by lameness. *Applied Animal Behaviour Science,* 67: 111–125.

Zuidhof, M.J., Schneider, B.L., Carney, V.L., Korver, D.R., and Robinson, F.E. (2014). Growth, efficiency, and yield of commercial broilers from 1957, 1978, and 2005. *Poultry Science,* 93, 2970–2982.

An ear tag to measure grazing behaviour of dairy cows at pasture

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Abstract

In traditional farming systems, management methods relied on observing and intuitive decision-making by the farmer. This is increasingly difficult as animal numbers have increased and farmer's available time has decreased. But animal localization and monitoring systems are being developed that can support or replace direct visual observations. One such system is the SMARTBOW (Weibern, Austria) ear tag incorporating a 3-axis accelerometer and battery, with the claimed advantage of compactness and long battery life. The ear tag measures cow head and ear movement during, e.g. grazing. This monitoring and measuring system can capture an activity budget for the individual cow over the 24 h day. This ear tag has been implemented on commercial farms where cows are housed indoors, but research is required for its deployment on animals in pasture-based systems. Such work is on-going in Ireland and Minnesota, USA. The system was installed at Teagasc Moorepark in March 2017. Behavioural data of cows (grazing times) were collected by visual observation, as the reference method, and by deployment of the SMARTBOW ear tag. Specific algorithms were developed for cow behaviour measurement within a pasture-based system. Subsequently, a study was conducted to evaluate the SMARTBOW ear tag, including the newly developed algorithms, using RumiWatch as the reference standard. The SMARTBOW and RumiWatch systems recorded grazing times for 778 h at the Teagasc Moorepark location. Agreement between the SMARTBOW and RumiWatch for grazing behaviour was strong, with a Pearson correlation of 0.91 and a Spearman rank correlation of 0.84.

Keywords: accelerometer, ear tag, validation, grazing

Introduction

New technologies are rapidly becoming available which can allow measurement and exploitation of biological variation to improve resource efficiency. Some of these technologies can be applied to improve efficiencies in pasture-based systems. However, the market potential for technology in pasture-based systems is relatively small and time is required to stimulate innovation in technology to capture and exploit the variation in pasture production and utilization. Because grazing is arguably the cheapest source of ruminant livestock feed, it is furthermore perceived by consumers as being natural and welfare friendly. The field of Precision Livestock Farming has already had a big impact in intensive dairy production, and the approach has the potential to bring tools to grazing management that will improve production efficiency as well as animal health and welfare.

With increasing scale on farms, and declining available labour, there is a requirement for technologies that assist farmers in their day-to-day management. Animal management involves ensuring the health and welfare of the animals; reacting to certain events in the animal reproductive cycle and improving efficiency in feed provision for conversion into an animal product, such as milk or meat. Especially in a pasture-based system, the balance between the feed offered and the herd demand needs to be optimised to maximise grass utilisation while simultaneously ensuring that animals are well fed. Shortage in labour

and time to observe animals makes it difficult for farmers to monitor all animals intensely. Automated monitoring for quantifying physiological and behavioural parameters, e.g. oestrus, somatic cell count and feeding behaviour, can give an insight into overall health status, important animal events as well as helping with feeding management. For continuous monitoring of these physiological and behavioural parameters, sensor-based easy-to-use tools need to be developed.

One of the best indicators of health and welfare of dairy cows is feeding behaviour. A study by Bareille *et al.* (2003) showed that feed intake was influenced by a number of different diseases such as milk fever, ketosis or hoof lesions. There is a benefit to detect emerging diseases earlier by monitoring the feeding behaviour of dairy cows automatically. Feeding behaviour can also be used to optimise grassland management decisions with a focus on increasing animal intake and reducing grass residuals. It is of key importance to measure, manage and allocate accurately the feed available and offered to the cows, in order to optimise farm efficiency and profitability. The estimation of feed intake based on behavioural parameters, such as feeding time or bite frequency, provides valuable information that can be used to manage cows. One approach previously used to determine feed intake was the IGER animal recording system (Mezzalira *et al.,* 2014). This consisted of a noseband sensor that measured jaw movement by electrical resistance (Rutter *et al.*, 1997). It could identify and measure grazing and rumination. However, the maximum recording period of this system was 24 hours, and the analysis of the data via the "Graze software" was very laborious (Rutter, 2000). Furthermore, the distribution and commercial support for this technology has ceased in recent years. But a new technology, the RumiWatch System may have the potential to improve data capture and replace the IGER animal recording system. However, this is an expensive system that may be more suitable for research rather than for everyday use on-farm. An ear tag accelerometer system (SMARTBOW GmbH, Weibern, Austria) is being developed for grazing behaviour. This ear tag is easy to attach and is not expensive. The objectives of this study were to develop a grazing algorithm for an ear tag and to validate the ear tag for grazing behaviour.

Materials and methods

This study was conducted at the Teagasc, Animal & Grassland Research and Innovation Centre in Moorepark, Fermoy, Co. Cork, Ireland and also with the grazing dairy cow herd at the University of Minnesota, USA. While the Irish part of the study is reported here, the similarly designed US part of the study is reported at the 2019 ADSA conference.

Ear tag description

The SMARTBOW ear tag can monitor estrus and rumination using acceleration data captured from the ear and head movements. The hypothesis is that the ear tag can also classify data into grazing and non-grazing behaviours.

Development of a grazing algorithm for the SMARTBOW ear tag

During May and June of 2017, ear tags were attached to grazing cows and three observers visually recorded behaviours for a total of 150 hours. The observational data from Ireland and additional data from Minnesota were used to create a master dataset. Two-thirds of the data were used for training the data and developing a grazing algorithm and the remainder were used for testing the ear tags' grazing algorithm.

To validate the developed SMARTBOW ear tag grazing algorithm, a halter with an integrated noseband pressure sensor (RumiWatch, Itin and Hoch GmbH, Liestal, Switzerland) was used.

RumiWatch halter and noseband

The RumiWatch comprised of a 3-axis accelerometer which recorded acceleration patterns and a noseband pressure sensor which detected jaw movements according to chewing activities. A study by Werner *et al.* (2018) showed that the RumiWatch halter and noseband can accurately record the grazing behaviour of a dairy cow with 92% accuracy.

Validation of grazing behaviour

During September of 2018, cow behaviour data were collected by the SMARTBOW ear tag and RumiWatch halter system from 15 Holstein Friesian cows in Ireland. The SMARTBOW ear tag and RumiWatch halter data were compared for number of grazing minutes per hour.

Experimental management

Cows were selected according to similarity in breed, lactation number and days in milk (DIM). These were Holstein Friesian multiparous cows (3, 4, 5 lactations) with an average DIM of 206 at the start of the study. Cows were milked twice daily and average daily milk yield per cow was 25.4 kg. Cows were milked in a Lely Astronaut A4 milking robot and received 3 kg/day of concentrates, during the milking process.

The grass offered to cows was of the ryegrass (*Lolium perenne*) variety. It had an average dry matter of 19%. Grass height was measured using a Grasshopper rising plate meter (True North Technologies). Average pre-entry and post exit (of cows) grass heights were 10 cm and 4 cm, respectively. Paddocks into which cow entered for grazing had average herbage mass of 1,330 kg DM ha^{-1}. A 4-way grazing system was operated, where cows were allocated a new grazing area every 6 h. This was put in place to assist cow-flow to the milking unit, as cows had to pass through the robot in order to gain access to the new pasture on each occasion. Thus, cows had the opportunity to be milked when passing through the robot yard and milking frequency could be maintained at twice per day.

All 15 cows were fitted with a SMARTBOW ear tag and a RumiWatch halter, including the noseband pressure sensor, for eight days, starting on 18 September and remained on the cows until 26 September. An adjustment period of 24 h was allowed before experimental data collection. Cows were monitored closely during this period to ensure that cows had adapted to the ear tag and halter before proper data collection. Cows were also monitored closely over the duration of the data collection period to ensure that the halter and noseband, in particular, were not having any adverse effects on the cows. Complete sets of data were obtained from 9 of the 15 cows. Extra cows had been used on the trial to allow for equipment issues for the cows or gaps in data capture. Mean air temperature was 12.4 °C and a total of 25 mm of rain/precipitation was recorded over the eight day period.

Data analysis

The data were downloaded from the ear tag and halter to a tablet. All RumiWatch data were converted using the RumiWatch converter 7.4.13, into 1 h summaries. The converted data were then analysed. A random number generator was used to select three different time periods from the overall dataset of 778 h, for which data would be analysed. The time periods selected were 150 h, 248 h and 778 h. A 2-sided paired t-test was used to compare the percentage of time for grazing behaviours recorded by the SMARTBOW ear tag and RumiWatch halter. Pearson correlations and Spearman rank correlations evaluated associations between the SMARTBOW ear tag and RumiWatch halter for grazing behaviour. Grazing behaviour recorded by both systems was profiled over a 24 h period. Pearson and Spearman rank correlations were again calculated for the more intense grazing periods.

Results and discussion

Percentage of time (±SD) and 95% confidence intervals for grazing or no grazing during the overall time period recorded of 778 h, as captured by SMARTBOW and RumiWatch are shown in Table 1. The proportion of time spent grazing, as recorded by the SMARTBOW ear tag and RumiWatch halter was 34.8% (CI 32.1–37.5) and 35.6% (CI 32.9–38.3) during the 778 h recording period. Between SMARTBOW and RumiWatch the Pearson correlation for grazing was 0.91 (CI 0.90–0.92; $P < 0.01$) and the Spearman rank correlation was 0.84 (CI 0.82–0.86; $P < 0.01$) for the same time period of 778 h (Table 2).

Table 1. Percentage of time (±SD) and 95% confidence intervals for grazing or no grazing during different time periods recorded, as captured by SMARTBOW and RumiWatch

Recording period	Behaviour	SMARTBOW	95% CI	Rumi Watch	95% CI	Mean Difference	*P*-value for t-test
778 h	Grazing	34.8 ± 38.6	32.1–37.5	35.6 ± 38.7	32.9–38.3	-0.8 ± 16.2	0.16
	No grazing	65.2 ± 38.6	62.5–67.9	64.4 ± 38.7	61.7–67.1	0.8 ± 16.2	0.16

Table 2. Pearson correlation and Spearman rank coefficients for SMARTBOW and RumiWatch over recording periods of 150 h, 248 h and 778 h

Recording period	Pearson correlation and 95% CI	Spearman rank and 95% CI	*P*-value
778 h	0.91 (0.90–0.92)	0.84 (CI 0.82–0.86)	0.01

The mean difference in percentage of time recorded as grazing by SMARTBOW and RumiWatch were very similar ($P = 0.75$, 0.25. 0.16). The standard deviation although large, is derived from the data being skewed as can be seen by the percentage of time spent not grazing at 65% (Table 1). The 150 h and 248 h datasets were also analysed but no notable differences were found either between 150 h, 248 h and 778 h.

A profile of daily cow grazing was established by calculating the average minutes spent grazing during each hour of the day. This data is shown in Figure 1. This may be used to identify times of more and less intense grazing over the full day. Figure 1 shows that there are very few hours (approximately 4-5 h) when cows grazed for more than 31 minutes h^{-1} (> 50% of each hour). However, cows graze on average up to 8 h of their day (Kilgour, 2012), and spend the remainder of the day at behaviours other than grazing. In order to investigate similar grazing intensities, a criteria of > 26 min h^{-1} was applied, i.e. the hours when cows spent > 26 min h^{-1} grazing were identified (Table 3).

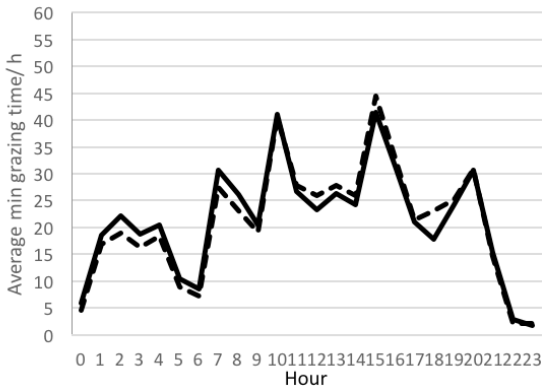

Figure 1. Profile of hourly grazing time during the day as measured by RumiWatch (—) and SMARTBOW (----), on the 778 h dataset

As observed in Figure 1, the times of most and least grazing intensities coincide for both the RumiWatch and SMARTBOW measurements. The hours with > 26 min grazing were selected and the RumiWatch and SMARTBOW were in agreement on these hours. The grazing pattern of the herd did show some variation. This may have been due to the fact that cows were being rotated every six hours to a new paddock and had different milking schedules. This inconsistency could have caused lower agreement than expected because the average min h^{-1} as displayed in Figure 1 were averaged over the eight days when data were collected. This average may not exactly reflect the everyday patterns. Typically, cows would come up to the parlor and return to pasture and start grazing for 1 - 2 hours after milking.

When the eight hours of maximum grazing observed were selected in each dataset, the grazing times as measured by RumiWatch and SMARTBOW were correlated and shown in Table 3. Measurement of grazing behaviour can sometimes be difficult, as the behaviour of grazing may be considered as both active and eating behaviours because cows may graze while standing or while walking. However, very strong agreement between grazing measurements with RumiWatch and SMARTBOW were observed in this study.

Table 3. Correlations of hours spent grazing during the day

Recording period	Time of day, hours	Pearson correlation and 95% CI	Spearman rank and 95% CI	*P*-value
778 h	7, 10, 11, 13, 14, 15, 16, 20	0.86 (0.82–0.89)	0.82 (0.78–0.86)	0.01

Conclusions

Both the RumiWatch halter system and the SMARTBOW ear tag were in agreement for monitoring grazing. Thus, the SMARTBOW ear tag can accurately monitor grazing behaviour in a pasture-based system. Although this algorithm is not commercially available yet, there is potential for the ear tag to be utilised in pasture-based dairy production systems to support farm management decision making.

References

Bareille, N., Beaudeau, F., Billion, S., Robert, A. and Faderdin, P. (2003). Effects of health disorders on feed intake and milk production in dairy cows. *Livestock Production Science,* 83: 53–62.

Kilgour, R.J. (2012). In pursuit of "normal": A review of the behaviour of cattle at pasture. *Applied Animal Behaviour Science,* 138: 1– 11.

Mezzaliraa, C., De Faccio Carvalhoa, P.C., Fonsecaa, L., Bremma, C., Cangianob, C., Leandro, H., Emilio, G. and Laca, A. (2014). Behavioural mechanisms of intake rate by heifers grazing swards of contrasting structures. *Applied Animal Behaviour Science,* 153: 1–9.

Rutter, S.M., Champion, R.A. and Penning, P.D. (1997). An automatic system to record foraging behaviour in free-ranging ruminants. *Applied Animal Behaviour Science,* 54: 185–195.

Rutter, S.M. (2000). Graze: a program to analyze recording of the jaw movements of ruminants. *Behavior Research Methods, Instruments, & Computers,* 32: 86–92.

USDA (2016). National Agricultural Statistics Service. United States, Government Printing Office, Washington.

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