803. A data-architecture to monitor and collect cow-individual methane emissions real-time from commercial dairy farms

I. Hulsegge*, D. Schokker, G.G.J. Klandermans and C. Kamphuis

Wageningen University & Research, Animal Breeding and Genomics, P.O. Box 338, 6700 AH Wageningen, the Netherlands; ina.hulsegge@wur.nl

Abstract

Real-time monitoring and collecting cow-individual methane emissions will help individual farmers in identifying which management interventions affect methane emissions, and the dairy sector in developing strategies to reduce methane emissions. To achieve this real-time monitoring and collecting of cow-individual methane data, an architecture was developed that automates both aspects in a commercial setting. The first step in the data architecture was to collect the analogue signal of sniffers real-time, and transform this signal into methane concentrations. Because these sniffers do not record cow identification, the second step was to combine the methane concentration data with real-time cow identification. The cow identification is retrieved by automatically detecting the ear tag in a live-stream video footage, to subsequently 'read' the 4-digit number of that ear tag. With the deployed architecture, we developed a universal, low-tech, and scalable method to collect cow-individual sensor data real-time for technologies that do not record cow identification by default.

Background

Precision Livestock Farming (PLF) includes the integration and interpretation of relevant sensor information leading to new opportunities in the management and breeding of livestock through continuous real-time monitoring of health, behaviour, production, reproduction, and environmental impact (Berckmans 2017; Herlin *et al.* 2021). PLF technologies are entering the livestock domain in a fast pace, offering the potential to collect information that was not possible a decade ago (Buller *et al.* 2020). Currently, PLF technologies are available to monitor greenhouse gasses (GHG) emissions at cow-individual level (de Haas *et al.* 2021). One of these technologies is a non-dispersive infrared unit or 'sniffer' to measure GHG emission (de Haas *et al.* 2021). These relatively cheap sniffers offer opportunities to meet the Dutch government's objective to reduce GHG emissions by 49% by 2030, compared to 1990 levels (Goverment of the Netherlands 2021). Real-time monitoring of cow-individual methane emissions will help in identifying which management interventions affect methane emissions (e.g. new feeding ration), and in developing strategies to reduce methane emissions in the dairy sector (e.g. through breeding). Currently, the methane emission measurements with sniffers take place in the milking robot as described by Huhtanen *et al.* (2015), which enables information to be collected on each individual cow. The sniffer monitors a constant analogue signal that is linearly related to gas concentrations, which can be transformed into a methane and carbon dioxide concentration. The sniffer measures continuously, and the assumption is that when a cow is in the milking robot and eating her concentrates while being milked, that the sniffer is measuring that cow's methane concentration. At a later stage, sniffer data and robot data are combined to add cow identification to sniffer data. To collect sniffer information real-time, the first step of our data-architecture involves the connection of the sniffer to an Arduino, a small and inexpensive computer and accompanying software to program this computer (https://www.arduino.cc). The Arduino is programmed to push the sniffer data to the cloud service platform Azure (https://azure.microsoft.com) via the Internet of Things (IoT) network. This IoT system was selected to avoid potential problems with low coverage of e.g. a WIFI signal (Schokker *et al.* 2020), allowing future upscaling independent of WIFI coverage. In Azure, an IoT hub was built which was subscribed to the data stream. This means that this IoT hub was used to acquire and ingest (load), and transform the raw sniffer analogue signal into a methane concentration data point. At this stage, we

DOI: 10.3920/978-90-8686-940-4_803, © I. Hulsegge *et al.* 2022

thus have cow-individual methane concentrations measured and collected in real-time. However, sniffers do not record cow identification, and thus, the next step of our data-architecture involved the real-time information which cow the sniffer is actually monitoring.

Automatic and real-time animal identification

Animal identification, which refers to the process of accurately recognizing individual animals, plays an important role in automatic and real-time analysis of activities and productivity in PLF. All cows in the Netherlands are uniquely identified with a lifetime registration number at birth. This number is printed on the ear tags that cows are obligatory to wear. Four digits of this ear tag are highlighted using a larger font size. These four digits are typically used by farmers as the cow's work number. In addition to these mandatory ear tags, Radio Frequency Identification Device (RFID) transponders that are connected to the neck-collar of the cow are also a method readily used to identify cows (e.g. RFID is used by milking robots for cow identification). However, not all farmers have milking robots. Also, milking robots may store the transponder identification together with a datetime stamp, but accessing and matching this identification to other data is not always straightforward, and therefore error-prone. Identification of animals by automatically reading the ear tags may be a more universal solution in precision dairy farming. This automation can be done using video footage or camera images. Methods for individual cow identification system using ear tags were described by Ilestrand (2017) and Zin *et al.* (2020). These methods have been applied on a static dataset of previously collected images. But for PLF, a system is required that continuously reads the ear tag number and makes this cow identification available real-time. The use of video is an attractive approach to achieve this because it offers 24/7 monitoring, and is a relatively cheap investment. We developed a system that enables real-time cow identification through the use of vision technology and artificial intelligence (AI). The system was developed and implemented in Python 3.8 using the Open Computer Vision Library (OpenCV 4.1.2), an existing library for the analysis of image or video datasets in AI and deep learning (Culjak *et al.* 2012). The system 'detects' the ear tag area from a live-stream, 'segments' the ear tag area from the live-stream, 'improves' the image quality using image processing techniques, 'rotates' the ear-tag such that the baseline of the tag is horizontal in the image, and subsequently 'reads' the 4-digit number of the ear-tag by applying a number recognition model. This whole process is depicted in Figure 1. The number recognition model was developed by transfer learning of a pre-trained household number model (Goodfellow *et al.* 2014), a Convolutional Neural Network (CNN) classifier. Recognizing house numbers is a quite similar problem to recognizing ear tag numbers. The house number model is retrained with ear tag numbers, which increased the accuracy of a test set from 80% using the pre-trained model to 87% using the retrained model. The developed data-infrastructure consists of a video station involving a Raspberry Pi 4 Model B (a small, inexpensive computer developed by the Raspberry Pi Foundation in the United Kingdom), connected to a security camera (DS-2CD2T43G0) via ethernet (LAN) connection. The video station is installed in the milking robot as a place where also the sniffer sensor is continuously recording the analogue signal. The Raspberry Pi is programmed to collect, and process the live-stream of the camera, to push just the ear tag number together with a timestamp to the Arduino where the methane data is also collected. From the Arduino the methane data, ear tag number and timestamp are streamed onto the Azure cloud platform using Azure Streaming Analytics (Figure 1). Streaming Analytics is a querying, alerting and monitoring tool that monitors data streams.

Challenges

At this stage, sniffer and ear tag data streams come-in simultaneously and (near) real-time in the cloud platform. However there are still challenges to overcome. The next step will be to integrate and synchronize the sniffer- and ear tag data streams real-time. Furthermore, during a cow's visit to the milking robot the ear tag is not always (clearly) visible, especially if the cow is moving her head. As a result, ear tag recognition is not robust enough to deduct the starting- and/or end-time of the robot visit. To overcome this problem

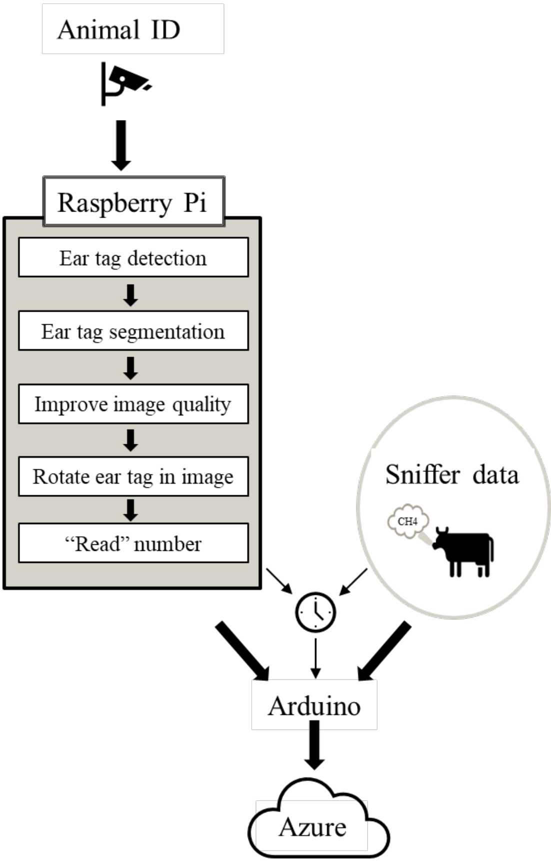

Figure 1. Schematic overview infrastructure.

template matching will be used to check if there is a cow in the milking robot, and to signal the starting and endpoint of a cow visit. Improvement in the downstream process, after 'reading' the 4 digits need also to be investigated. One of current investigation is to improve the number recognition by comparing consecutive predicted numbers in time. Such a system could be developed by using a majority vote of the prediction for in a sliding window of consecutive frames. Other improvements could be made by comparing the predicted number with a list of all cow ear tag numbers present in the herd.

Conclusions

A universal, low-tech and scalable method to collect cow-individual sensor data real-time for technologies that do not record cow identification by default is developed and deployed in a commercial setting. The system can be applied anywhere on a farm, not just in the milking robot as described in this paper. The method offers perspective to be used by other PLF techniques that do not register animal IDs by default. The data architecture is flexible in accepting additional data streams, e.g. other sensor data, but also animal and farm data that are often stored in separate farm management systems. Another part of the flexibility of the infrastructure links to the scalability, i.e. handling data from new farms in case the number of farms where methane is monitored, increases (Schokker *et al.* 2020).

Acknowledgements

This research was conducted by Wageningen Livestock Research, commissioned and funded by the Dutch Ministry of Agriculture, Nature and Food Quality, within the framework of Policy Support Research theme 'Data Driven & High Tech' (project number KB-38-001-004).

References

Berckmans D. (2017) Animal Front. 7(1): 6-11. https://doi.org/10.2527/af.2017.0102

Buller H., Blokhuis H., Lokhorst K., Silberberg M. and Veissier I. (2020) Animals 10(10): 1-12. https://doi.org/10.3390/ani10101779

Culjak I., Abram D., Pribanic T., Dzapo H. and Cifrek M. (2012) A brief introduction to OpenCV, pp. 1725-1730 in *35th MIPRO*, Opatija, Croatia.

De Haas Y., Veerkamp R.F., De Jong G. and Aldridge M.N. (2021) Animal. https://doi.org/10.1016/j.animal.2021.100294

Goodfellow I.J., Bulatov Y., Ibarz J., Arnoud S. and Shet V. (2014) Multi-digit number recognition from street view imagery using deep convolutional neural networks, pp. in *2nd ICLR*. International Conference on Learning Representations, ICLR, Banff, Canada.

Goverment of the Netherlands (2021) Climate policy, pp. Available at: https://www.government.nl/topics/climate-change/climate-policy.

Herlin A., Brunberg E., Hultgren J., Högberg N., Rydberg A. *et al.* (2021) Animals 11(3): 1-20. https://doi.org/10.3390/ani11030829

Huhtanen P., Cabezas-Garcia E.H., Utsumi S. and Zimmerman S. (2015) Comparison of methods to determine methane emissions from dairy cows in farm conditions, pp. 3394-3409 in *J. Dairy Sci.* Elsevier Inc.

Ilestrand M. (2017) Automatic Eartag Recognition on Dairy Cows in Real Barn Environment, pp. 55.

Schokker D., Mollenhorst H., Seigers G., De Haas Y., Veerkamp R.F. *et al.* (2020) Real-Time Visualization of Methane Emission at Commercial Dairy Farms, pp. 194-200 in *13th IFIP WG 5.11 International Symposium on Environmental Software Systems, ISESS 2020*, edited by Athanasiadis I.N., Knibbe W.J., Frysinger S.P. and Schimak G. Springer.

Zin T.T., Pwint M.Z., Seint P.T., Thant S., Misawa S. *et al.* (2020) Sensors 20(12): 1-18. https://doi.org/10.3390/s20123564