

Acceleration Measurement Experiments in Dairy Cattle

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Abstract— The great challenge of our time is monitoring of the condition of our farm animals, which is made possible by IoT technologies. This segment of agriculture is called IoF, Internet of Farms. This article presents the preliminary experiments in bolus sensor development. Many physiological and behavioral characteristics of cattle can be monitored by recording and analyzing data from an external three-axis accelerometer placed on the cattle's body.

Keywords—IoF, accelerometer, dairy cattle, data science

I. INTRODUCTION

Automation and digitalization are trends in animal husbandry today[1]. This process is often referred to as IoF, Internet of Farms [2]. This covers that animals are instrumented with different sensors, allowing them to be monitored continuously. This innovation not only helps livestock farms to manage their workforce, but also helps farms to keep their animal welfare in focus, including good health, housing conditions and the management of heat stress, which is increasingly affecting animals as a result of global warming. In the case of dairy cattle, we often speak of sensors placed on the legs, neck, tail, or rectum, or possibly combinations thereof [1]–[9]. External sensors placed on the animal are very problematic in animal husbandry because they are picked up by the animals or can be damaged during their daily movement. To prevent this, boluses placed in the rumen of cattle have also recently appeared. With the development of technology, the goal would be to develop tools that can accompany the life of an animal, perform complex measurements and often provide complex analysis of the condition of animals. In line with this trend, we performed experiments to investigate which physiological and behavioral characteristics of dairy cattle can be identified with a three-axis accelerometer. The ultimate goal is to develop a bolus that can perform complex measurements and complex analysis from the measured data, helping to detect estrus, heat shock, the onset of calving, and to assess overall animal welfare. One of the planned components of this complex measuring instrument is the three-axis accelerometer, which, together with the experimental device, would be

introduced into the rumen of cattle. In the preliminary experiments, unfortunately, neglecting the movements of the rumen, the sensors were placed to the side of the cattle and tried to collect as many behaviors that could be identified with an accelerometer. Thus, our research question was what elementary behaviors and events can be collected using a bolus sensor, which can be the input data of a complex evaluation system, even including artificial intelligence solutions.



Figure 1. Sensor unit with 3 axes accelerometer

II. METHODS

The experiments were performed on the Etyek farm. The identifiers (ear numbers) of the cows used in the experimental set-up were recorded. In all cases, the experiment was performed with healthy dairy cows.

Experiment I.

Devices used for the first experiment: Sensor unit with Bosch BMA180 three-axis acceleration sensor, in which the sample rate can be adjusted between 20 Hz and 2400

Hz and sensitivity can be adjusted between 1 G and 16 G. Wireless communication was implemented the 802.15.4 protocol with 250 kbps in the 2.4 GHz band. The sampling frequency was 600 Hz. The unit was powered from an 18650 LiIon cell.

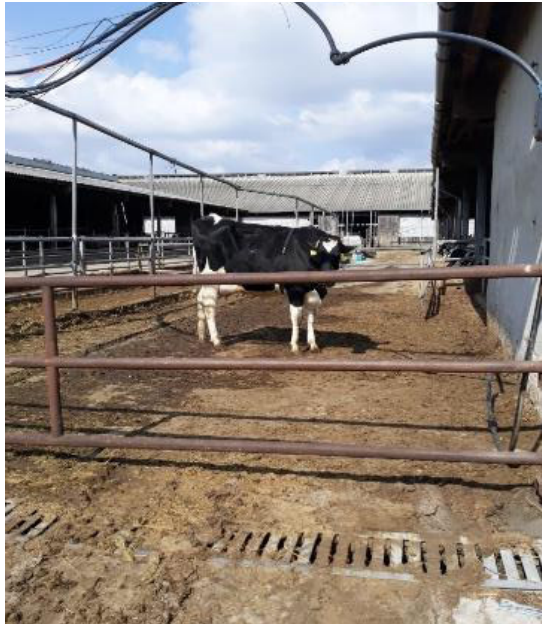


Figure 2 Dairy cow in the 1st experiment in a paddock. The sensor is attached to the side with a strap.

The receiving side: it was a 2.4 GHz data radio, the data was recorded with a laptop. Meanwhile, video was recorded with a GoPro Hero 3 camera, and video and accelerometer measurements were time-synchronized. The structure of the measured data set is shown in Figure 3.

..1, ..1618991182.550546449, ..2464, ..3947, ...676, ..1578
..1, ..1618991182.550546449, ..2465, ..3949, ...707, ..1620
..1, ..1618991182.550546449, ..2466, ..3955, ...727, ..1686
..1, ..1618991182.550546449, ..2467, ..3946, ...721, ..1695
..1, ..1618991182.550546449, ..2468, ..3936, ...738, ..1737
..1, ..1618991182.550546449, ..2469, ..3914, ...716, ..1766
..1, ..1618991182.550546449, ..2470, ..3901, ...701, ..1834
..1, ..1618991182.550546449, ..2471, ..3869, ...733, ..1888
..1, ..1618991182.550546449, ..2472, ..3837, ...727, ..1940
..1, ..1618991182.550546449, ..2473, ..3810, ...697, ..1983
..1, ..1618991182.550546449, ..2474, ..3804, ...669, ..2037

Figure 3: Data format: Sensor ID, Timestamp, Buffer serial number, Acceleration in X, Y and Z directions

In a group, 16 data have the same timestamp, the time distribution of measurements is uniform, but the data is congested and several packets are lost, so a subsequent correction was required, the steps of which

- Chronological backward timestamp correction according to the buffer sequence number
- Possible interpolation of missing data based on buffer sequence numbers
- Modify the timestamp with a constant value, align it with the video.

Unfortunately, the noise of the measurements was very large, so in each case it was necessary to correct this,

which was solved by averaging the data of the 16-member data buffer sent in units. With this we were able to get a roughly smoothed baseline.

During the data processing, the time synchronization of video recording had to be solved. During recording, synchronization points were added to the video, then a visible timestamp is added to the frames.

During the statistical processing of the data, the timestamp of the data records had to be corrected based on the buffer number, as in several cases congestion developed on the receiving side and the storage of the data was delayed. In addition, several data packets were lost, which were replaced by linear interpolation based on the existing data if the statistical processing algorithm could only process a complete data set.

When processing the video, the video was manually annotated according to the observable behaviors. These are: standing, walking, rumination, stepping, other, Unobservable behaviors: lying, drinking, eating, extreme movements.

In the statistical processing, the resulting vector was calculated, from which - histograms were made Block-by-block scattering and its evaluation is the blending of motion information and video.



Figure 4 Lying data logger with the cattle ID

Experiment II.

Animal: three cattle, identified by ID wearing on the ears that were in a stable within the Etyek farm during the experiment

Methodology: The experimental device was strapped to the animal and the data from the device were recorded for 2 days, in parallel, the lying position counter (HOBOPendant G Data Logger unfiltered, Onset Computer

Corp., Bourne, MA) [9] attached to the legs of the animals recorded the lying position for all three animals. Device: Measuring instrument is the same as described in the experiment 1st. Sampling frequency was 300Hz, data was recorded with a Raspberry Pi 3B computer with the settings and data format described in the experiment 1st. During the processing, no video was made, but we were able to separate the time spent by each animal with lying with help of the recorded data series provided by the lying position counter. Thus, this series of measurements is suitable for separating the lying position from other movements.

III. RESULTS AND DISCUSSION

As a result of the first experiment, a set of data with acceleration values and timestamps was available, as well as video recording for the same period, which was manually categorized by behavior, distinguishing between standing, walking, stepping, ruminant, and other categories. The streamed graph of the measured data set was copied to the video recording. Figure 5 shows the measurement result. The image of the current video corresponds to the value of 0s in the graph. The graph in Figure 5 shows the standard deviation within the data buffers containing 16 data. In the graphs, standing and walking behavior can be well separated. Unfortunately, rumination cannot be identified with these studies. Feeding and drinking were not available for the cow in the paddock, so eating and drinking behavior patterns could not be observed.

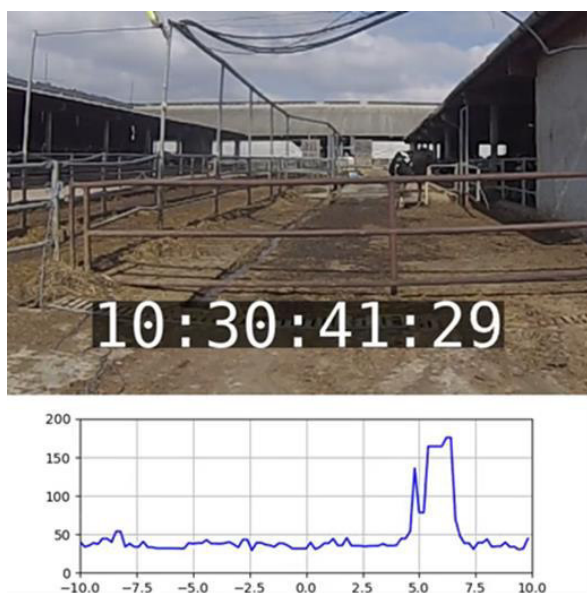


Figure 5 The timeline and the graph made from the sensor data stream were added to the video taken in the paddock.

As this paddock does not give the cow enough comfort, the cow remained standing throughout the study period. Thus, it was not possible to detect the lying position either.

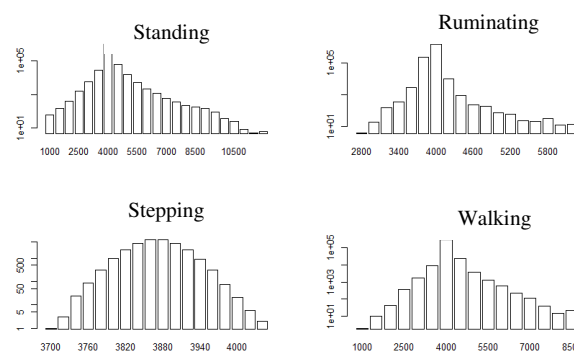


Figure 6 Histogram of the resultant acceleration values for four different modes of motion

The resultant acceleration from the acceleration values measured on the three axes was calculated. The resultant acceleration values were plotted on a histogram. Due to the setting of the device, the possible values of the resultant acceleration were in the range of 0-8000. Figure 6 shows that the histograms have also maximum for the three forms of motion at 4096, namely standing, ruminating and walking. The value of 4096 corresponds to a value of 1G of the ground gravity acceleration. Because the animals have a fairly large body weight, they perform the movements with relatively small relative accelerations. Only stepping as a behavior can be distinguished from other movements based on a histogram because the resulting acceleration averages 3850, which corresponds to 0.94G. From the histogram, it can be seen that the 2-fold standard deviation is within the intervals of 1000 and 7000. Thus, it will not be necessary to change this initial setting during the subsequent setting of the sensor.

Figure 7 shows the result of the second experiment. In this experiment, it was possible to observe the acceleration values measured in the lying position of the animal. The figure shows the acceleration values measured on the y and z axes. Acceleration values measured in lying position are indicated in green and those measured in other body positions are indicated in red. Besides a few outliers, red and green points, corresponding to the two categories, can be linearly separable. Unfortunately, as no additional sensors were available and no video capture was possible, it was no way to identify additional behavioral categories on the measured data set. The basis for position identification is that the angle of inclination of the sensor attached to the side of the animal is 20-30 ° when lying down.

Since the position of the sensor has changed at lying, this position could be separated from the other body positions. In the experiment, the sensor rotates when the cattle lying down.

Unfortunately, the sensor placed on the animal can be moved. In this case, the consecutive horizontal and non-horizontal positions can be distinguished because the angle of inclination of the sensor changes, but it is not possible to assign absolute acceleration values to the

lying position or the other positions. Unfortunately, in the case of a rumen bolus, a similar case must be occurring. In the rumen of the animal, the sensor can move easily. With proper techniques, the sensor can be mounted around roughly one axis, the vertical axis, but this can make it difficult to detect the position later on.

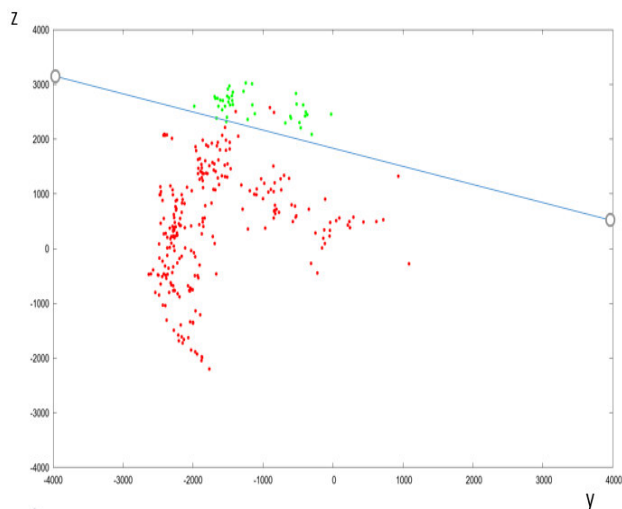


Figure 7 The horizontal and vertical positions can be clearly distinguished by considering the acceleration values measured along the y and z axes.

IV. CONCLUSION

The article reviews and evaluates preliminary experiments of a rumen bolus accelerometer sensor. The sensor should make it possible to identify individual movements and behaviors. Based on this, the locomotor activity and activity of the experimented animals can be precisely determined and quantified. In subsequent experiments, some important health and animal husbandry characteristics of the animal can be identified on this basis. As well as on the basis of additional sensor data and other information collected about the animals, using data analysis methods that also use artificial intelligence. The primary goal is the accurate and rapid identification of health problems, estrus and parturition. In the presented experimental setup, the following forms of movement could be identified: standing, walking, stepping in a standing position, lying down. Eating, drinking, rumination, and increased locomotion activity indicating estrus were not detected in this experiment. The interpretation of the experiments was disturbed by the fact that the sensor was fixed to the side of the animal, so that the position of all three axes of the accelerometer relative to the animal was constant during the experiments. Later, it can be expected that the sensor can move freely in the rumen of the animal, with a maximum of one vertical axis that can be fixed in the absolute sense. In the next phase of the research, it is worth placing some bolus sensors in the cow's rumen and extracting native, measured data from it, as well as for a short time. A short time is a period of about 30 days because it contains at least one cycle of estrus of the cow.

It is a good idea to follow the experiment with external validation tools. Ideally, this could mean making a video with a suitable camera system. Based on this, the behavior of the cow can be accurately categorized. Less valuable but usable results can be obtained by equipping the cow involved in the bolus experiment with bed counting, ruminant, and estrus sensors. In the first case, all important behaviors (standing, walking, lying, jumping, ruminating, eating, drinking) can be identified, while in the second case, only a reduced number of categories can be evaluated.

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