## Real-Time Classification of Cattle Behaviour using Accelerometer Sensors

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### Abstract

In this study, we develop and validate a supervised machine-learning algorithm to monitor grazing and ruminating behaviours of cattle using accelerometer sensors. The method is specifically designed for performing real-time classification on resource-constrained sensor nodes. Twenty multiparous Holstein cows were used for this study. Each cow was wearing an AX3 accelerometer sensor attached to a neck-collar. The cows had daily access to a pasture between 7:30 AM and 2 PM for three weeks. Direct observations of the cows' behaviours were made to validate the sensor data. A new decision-tree algorithm (DT) was developed to classify the raw data. The decision-tree algorithm was selected for its low computational costs, which makes it implementable on the on-cow nodes. The DT presented an overall accuracy of 91% with a sensitivity and precision between 89-94% for ruminating and grazing behaviours. The hourly difference between the predicted and the observed (total) ruminating and grazing times (in min/h, mean±standard error) were 1.9±0.09 min/h (3.1% of the observed time) and 2.2±0.07 min/h (3.7%) respectively. This validation illustrates the potential of the collar-mounted accelerometer to classify grazing and ruminating behaviours.

**Keywords**: Accelerometer, dairy cows, machine learning, behaviours classification, precision dairy farming, grazing behaviour.

### Introduction

Changes in behaviours could provide relevant information about nutrition, (re)reproduction, health, and welfare of dairy cows. Progress has been made in monitoring cows with electronic and biosensor devices (Lee and Seo 2021). In particular, wearable accelerometers have been widely used to automatically assess cow behaviours (Chapa et al. 2020). For example, grazing and ruminating times were recorded using HOBO accelerometers attached to the cows' jaws (Rayas-Amor et al. 2017). Martiskainen et al., (2009) developed a method for automatically measuring and recognising several behaviours of dairy cows, including feeding and ruminating behaviours, based on a multi-class support vector machine (SVM). Although it yields high classification accuracy, it is well known that SVM require high computational costs (Abdiansah and Wardoyo 2015). In another study (Vázquez Diosdado et al. 2015), a decision-tree (DT) algorithm was used among other machine learning techniques to differentiate between lying, standing, and feeding behaviours with a neck-mounted accelerometer. The proposed algorithms did not consider ruminating behaviour and they also required a high sampling rate (50 Hz). Other studies (Greenwood et al. 2017; Kasfi, Hellicar, and Rahman 2016; Martiskainen et al. 2009; Smith et al. 2016) used algorithms with high computational load (e.g., deep learning), which could not be directly implemented on the on-cow sensor.

In practice, the on-cow sensors used for animal behaviour monitoring have very small batteries with low processing and storage capabilities. Furthermore, such batteries would need to operate properly and autonomously for long periods of time (e.g., five years) without being recharged or replaced; specifically for application on commercial farms. Therefore, data storage capability and energy consumption are important issues in using sensors for monitoring behaviour of dairy cows. A simple DT algorithm could be a crucial to reduce the energy consumption and maintenance requirements associated with recharging of batteries while maintaining acceptable performances.

In this paper, we validate a DT algorithm to monitor grazing and ruminating behaviours in dairy cattle using accelerometer sensors. This method, based on the DT, is specifically designed for performing classification in real time on resource-constrained sensor nodes. Consequently, it reduces the energy consumption and maintenance requirements associated with recharging of batteries while maintaining acceptable performances. The proposed algorithm and system further support the transition towards a continuous and large-scale monitoring of ingestive-related behaviour of dairy cattle.

## Material and methods

### Animals and housing

In total, 20 multiparous Holstein cows (milk yield 33.7 ± 3.5 kg/d; mean ± SD) were used in this study. Experiments were conducted between June and August 2020 at the Flanders Research Institute for Agriculture, Fisheries and Food (ILVO), Melle, Belgium. The cows had daily access to pasture between 7:30 AM and 2 PM for three weeks (grazing period). Drinking water was available ad libitum. Inside the barn, the cows were housed in an area compartment of 30 m long and 15 m wide with 24 individual cubicles and a concrete slatted floor. The cubicles (n = 24, 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 mixture of chopped straw, lime and water (Mader et al. 2017). The cows were fed roughage ad libitum and concentrates were supplied individually by concentrate feeders.

### Data collection procedure

Each cow was wearing an accelerometer sensor (Figure 1). The accelerometer was attached to the left side of the collar of each cow as shown in Figure 1. The acceleration data (i.e., 3 orthogonal accelerometer vectors) were logged with a sampling rate of 10 Hz (10 samples each second) using Axivity AX3 loggers (Axivity Ltd, United Kingdom). The clocks of the observer and the accelerometers were synchronized at the start of the measurement.

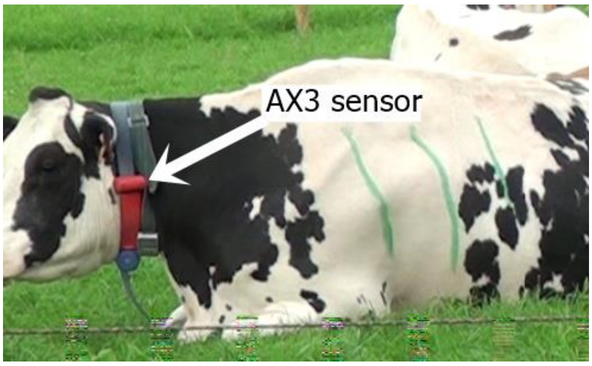


Figure 1. A cow wearing an AX3 sensor in the grazing field.

Observations on the behaviour of the cows were made directly in the grazing field by a trained researcher. Table 1 lists the behaviours recorded along with their descriptive definitions. Every one-minute time window was assigned a label to refer to grazing, ruminating, and other activity (not grazing and rumination), respectively, based on the most frequent behaviour in that minute. As 5 hours of visual observation were available for 20 cows, 6000 samples of observed behaviours were obtained (i.e., 6000 min).

Table 1. Description of the observed behaviours and the number of samples of each behaviour (Number of 1 min time intervals for each observed behaviour).

| Observed Behaviours | Description | Number of samples |
|---|---|---|
| Grazing | A cow has her muzzle close to or near the ground and is ripping the forage and chewing it (head position up and down). | 2220 (37 %) |
| Ruminating | A cow is chewing and swallowing a ruminating bolus while moving her head and jaw with a circular motion. | 2520 (42 %) |
| Other activity | Anything that was not grazing and rumination | 1260 (21 %) |
| Total (SUM) | | 6000 (100 %) |

Processing of sensors data

The data processing was performed using MATLAB software (Release 2019b, The MathWorks, Inc., Natick, Massachusetts, United States).

The accelerometer data (i.e., acceleration along X, Y, Z axes) were downloaded to a laptop and converted to .csv files using OmGui software version 1.0.0.43 (Newcastle University, UK). Similar to Benaissa et al. 2019, the acceleration sum vector ($A_{sum}$) was calculated as follows:

$$A_{sum} = \sqrt{{a_X}^2 + {a_Y}^2 + {a_Z}^2} \quad (1)$$

Where $a_X$ is the acceleration along the X-axis, $a_Y$ is the acceleration along the Y-axis, and $a_Z$ is the acceleration along the Z-axis.

Figure 2 shows a flow graph of the DT algorithm that was designed to distinguish between the three considered behaviours. As shown in Figure 2, the DT uses the overall dynamic body acceleration (ODBA) calculated from the $A_{sum}$ values as presented in Benaissa et al. 2017.

The thresholds of the DT (Figure 2) were determined using the nested cross-validation technique as explained in Benaissa et al. 2019. The mean value of 19 obtained thresholds were 0.033 g with a standard deviation of 0.001 for the threshold 1, and 0.013 g with a standard deviation of 0.002 for threshold 2. The coefficient of variation was 6 % for both thresholds. These low values indicate the general applicability of the thresholds for other cows.

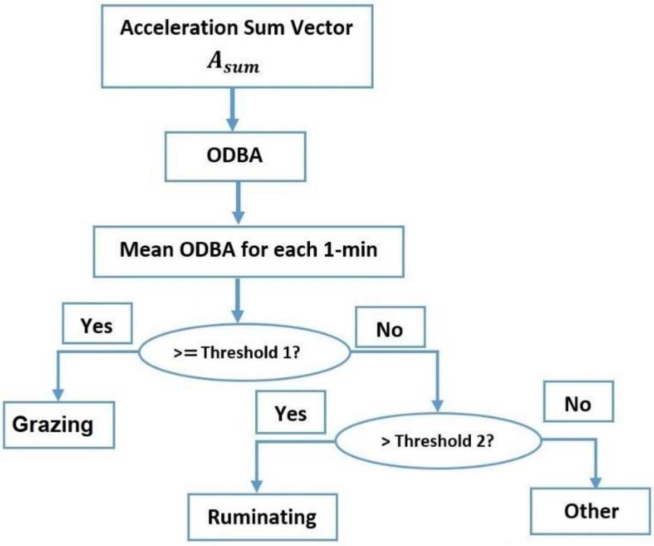


Figure 2. Classification approach using DT algorithm based on the overall dynamic body acceleration (ODBA). The scheme was designed to be implemented on resource-constrained embedded systems

Evaluation

To evaluate the classification algorithm, the precision, the sensitivity, the specificity, and the overall accuracy were used. In addition, the performance of the algorithm was evaluated in terms of the difference in ruminating and grazing times reported by the observations compared to the sensor. As explained in Benaissa et al. 2019, the leave-one-out cross-validation strategy was used to calculate the average precision, sensitivity and overall accuracy.

## Results and Discussion

The precision, sensitivity, and specificity of the DT algorithm for each considered behaviour are listed in Table 2. The sensitivity of ruminating (92%) and grazing (90%) was higher than that of other activity (83%). Similarly, the precision of ruminating (89%) and grazing (94%) was higher than that of other activity (82%). The specificity was similar for grazing (97%) and other activity (96%) and lower for ruminating (91%). The overall accuracy was 91%. Table 3 lists the absolute difference in ruminating and grazing times (in min/hour and in % of the observed time) between observation and sensor (predicted). The hourly absolute difference between the predicted and the observed ruminating time (in min/h, mean±standard error) was 1.9±0.09 min/h (3.1% of the observed time). For the difference in grazing time, 2.2±0.07 min/h (3.7%) was obtained. This means an error between 6.6 and 11 min, which is less than 4 % of the observed grazing time (the observed grazing time ranges from 3 to 5 hours). Similarly, based on Grant (2007), a lactating cow spends 7 to 10 hours ruminating. This means that the daily error of the DT algorithm ranges from 13 to 19 min. This is less than 3 % of the daily ruminating time. Thus, the proposed DT algorithm can accurately detect grazing and ruminating times.

Table 2. Precision, sensitivity, and specificity [%] of the DT algorithm for each behavioural class

| | Ruminating | Grazing | Other |
|---|---|---|---|
| Precision [%] | 89 | 94 | 82 |
| Sensitivity [%] | 92 | 90 | 83 |
| Specificity [%] | 91 | 97 | 96 |

Table 3. Absolute difference in ruminating and grazing times (in min/hour and in % of the observed time) between observation and sensor (predicted).

| | Ruminating time | | Grazing time | |
|---|---|---|---|---|
| | Difference in [min/h] | Difference in [%] | Difference in [min/h] (mean±SD) | Difference in [%] |
| Mean | 1.9 | 3.1 | 2.2 | 3.7 |
| Standard error | 0.09 | 0.15 | 0.07 | 0.12 |

## Conclusions

This paper validated a DT algorithm applied to data from a neck-mounted accelerometer to monitor grazing and ruminating behaviours of dairy cows. The calculation procedure and the thresholds of the DT provided in this work could be useful for rapid and real-time implementations on resource-constrained embedded systems. The proposed method allows a possible reduction of the power consumption of the sensors and enable a large-scale deployment of the monitoring system. Future work will address the estimation of the power consumption reduction and a possible deployment in commercial farms.


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