Classification of ingestive-related cow behaviours using RumiWatch halter and neck-mounted accelerometers

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Highlights

- Simple decision-tree (DT) algorithm to classify feeding and ruminating behaviours
- The DT performs similar to support vector machine and a RumiWatch noseband.
- The use of a simple DT would help implementing the algorithm on the on-cow sensor
- It would enable online measurements of the ingestive-related cow behaviours

Abstract

A new simple decision-tree (DT) algorithm was developed using the data from a neck-mounted accelerometer for real-time classification of feeding and ruminating behaviours of dairy cows. The performance of the DT was compared to that of a support vector machine (SVM) algorithm and a RumiWatch noseband sensor and the effect of decreasing the sampling rate of the accelerometer on the classification accuracy of the developed algorithms was investigated. Ten multiparous dairy cows were used in this study. Each cow was fitted with a RumiWatch halter and an accelerometer attached to the cow's collar with both sensors programmed to log data at 10 Hz. Direct observations of the cows' behaviours were used as reference (baseline data). Results indicate that the two sensors have similar classification performances for the considered behavioural categories (i.e., feeding, ruminating, other activity), with an overall accuracy of 93 % for the accelerometer with SVM, 90 % for the accelerometer with DT, and 91 % for the Rumiwatch sensor. The difference between the predicted and the observed ruminating time (in min/h) was less than 1 min/h (1.5% of the observed time) for the SVM and less than 2 min/h (2.8%) for both DT and the RumiWatch. Similarly, the difference in feeding time was 1.3 min/h (2.1%) for the SVM compared to 2.5 min/h (4.3%) and 2.4 min/h (4.1%) for both RumiWatch and DT, respectively. These preliminary findings illustrate the potential of the collar-mounted accelerometer to classify feeding and ruminating behaviours with accuracy measures comparable to the Rumiwatch noseband sensor.

Keywords: Behaviors classification; accelerometer; RumiWatch; dairy cows; machine learning; internet-of-animals

1. Introduction

Monitoring ingestive-related behaviours (i.e., feeding and ruminating) can yield important information about the health, productivity, and welfare of dairy cows. For instance, changes in the time a cow spends feeding and ruminating can indicate an underlying shift in cow comfort and welfare (Ledgerwood et al., 2010; Tucker and Weary, 2004). As reported by Urton et al., (2005), cows diagnosed with clinical and subclinical metritis spent less time ruminating than the healthy cows during both the pre- and post-calving periods. In addition, it is well accepted that changes in feeding and ruminating time could help farmers in predicting calving moments (Kok et al., 2017; Pahl et al., 2014; Schirmann et al., 2013), oestrus (Pahl et al., 2015; Reith et al., 2014), and lameness (Whay and Shearer, 2017). For example, Schirmann et al., (2013) stated that the cows spent, on average, 63 min (13 %) less time ruminating and 66 min (27 %) less time feeding in the 24-h period before calving. These behaviours continued to decline during the 24-h period after calving when, compared with baseline, time spent ruminating decreased on average by 133 min (27 %) and time spent feeding decreased by 82 min (34 %). By predicting the moment of calving, the farmer/veterinarian could assist the cow's calving and avoid risks of disease and mortality when the calving is difficult for the cow (e.g., dystocia). For oestrus detection, Reith et al., (2014) reported that the data of daily ruminating time were, on average, reduced by 19.6 % (83 min/d) on the day of oestrus. Predicting the cows in heat will increase the conception rate of the following artificial insemination (AI) and the productivity of the dairy farm. Similarly, it is shown by Norring et al. (2014) that lame cows spend less time feeding per day (e.g., 101 ± 4 min/d for lameness score 3, i.e., moderately lame). The detection of lameness in its early stages will significantly decrease the economic losses due to decreasing milk production and costs of veterinary treatment and avoid increased risk of culling (Barkema et al., 1994). However, monitoring the cows' behaviours with the traditional methods like direct observation or manual analysis of video recordings is time and labour consuming, especially in large-sized farms. Progress has been made in monitoring cows with electronic and biosensor devices (Benaissa et al., 2016a, 2016b; Braun et al., 2015; Chapinal et al., 2011; Dutta et al., 2015; Maselyne et al., 2017; Piccione et al., 2011; Van Nuffel et al., 2015). In particular, wearable accelerometers and noseband halters have been widely tested to automatically assess cow behaviours (Martiskainen et al., 2009a; Müller and Schrader, 2003; Robert et al., 2009; Vázquez Diosdado et al., 2015). For example, the RumiWatch noseband sensor was developed and validated as a monitoring device for ruminating and eating activities in stable-fed dairy cows (Braun et al., 2013; Zehner et al., 2017). In addition, grazing and ruminating times were recorded using HOBO accelerometers attached to the cows' jaws (Rayas-Amor et al., 2017). In the latter study, the tilt of the accelerometer axes was used for the classification. However, as explained in (Benaissa et al., 2017) , this method is impractical in real situations where a slight movement of the sensor could change the reported tilt of the axes within the same behaviour. For neck-mounted accelerometers, 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). It is well known that SVM requires high computational costs, although it yields high classification accuracy (Abdiansah and Wardoyo, 2015). In another study (Vázquez Diosdado et al., 2015), a decision-tree 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 et al., 2016; Martiskainen et al., 2009b; Smith et al., 2016) used algorithms with high computational load (e.g., multi-class binary classification, random forest, SVM, and neural networks), which could not be implemented on the on-cow nodes. Therefore, the raw accelerometer data should be transmitted to the backend system for processing, which leads to a high energy consumption and limits the battery lifetime of the sensors

In practice, the on-cow sensors used for behaviour monitoring (e.g., internet-of-things nodes) 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. Therefore, the storage and the energy consumption are important issues in using sensors for monitoring behaviour of dairy cows. To reduce the energy consumption and maintenance requirements associated with recharging of batteries while maintaining acceptable performances, using a simple DT algorithm with lower sampling rates could be a crucial solution for extending battery lifetime by reducing storage load and minimizing both sensing and transmitting energies. This may further support the transition towards a continuous and large-scale monitoring of the ingestive-related behaviour of dairy cattle

The objectives and novelties of this study were (i) to automatically classify ingestive-related cow behaviours (i.e., feeding, ruminating) based on a simple DT algorithm, (ii) to compare the performance of the DT with that of a SVM algorithm and a RumiWatch noseband sensor, and (iii) to investigate the effect of decreasing the sampling rate on the classification performances of the developed classification algorithms. In this study, relatively low sampling rates (0.5-10 Hz) were used. Also, to the best of our knowledge, no study has yet proposed a simple DT algorithm for real-time classification of ruminating behaviour based on neck-mounted accelerometers and compared it to a RumiWatch noseband sensor. Finally, collar-mounted sensors would be more advantageous for cost and convenience (Umemura et al., 2009).

2. Materials and methods

2.1 Animals and housing

Measurements were conducted between March and November 2017 in the dairy barn of the Flanders Research Institute for Agriculture, Fisheries and Food (ILVO), Melle, Belgium. From a group of 30 cows, ten different multiparous Holstein cows (milk yield 34.3 ± 4.8 kg/d; mean ± SD) were selected for this study. The cows were housed in area compartment of 30 m long and 13 m wide 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 mixture of cut straw, lime and water (Mader et al., 2017). The cows were fed roughage ad libitum and the concentrates were supplied by computerized concentrate feeders. Drinking water was available ad libitum. The cows had free access to a rotating cow brush. The cows had access to a milking robot via the feeding area and a smart selection gate in a feed-first cow traffic system. A cow was allowed access to the milking robot based on different parameters such as the interval since the previous milking, expected milk yield, and lactation stage.

2.2 Data collection procedure

Cow behaviours were monitored simultaneously with two sensors (i.e., RumiWatch noseband halters and accelerometers) and also by visual observations. The sensors were attached more than 24 hours before starting the measurements as recommended by Zehner et al. (2010). For each cow, sensor data were collected for 5 days. While the sensors were recording, 6 hours (10 AM to 4 PM) of direct observations were made for each individual cow during one of the 5 days. At the end of the data collection measurements, the data of both sensors (i.e., 5 days per cow) and the observations (i.e., 6 hours per cow) were downloaded to a laptop for processing. The collected data were used to construct two data sets. Data set 1 contained the data of the visual observation with the corresponding sensor data (6 hours per cow). This data set was used to train (i.e., build the classification model, find the thresholds) and test the performance (i.e., calculate the accuracy) of the DT and the SVM algorithms and to compare the two sensors to the visual observations. After optimizing the two algorithms (DT and SVM), data set 2, which contains the sensors data for 5 days per cow, was used to compare the two sensors for long term monitoring (i.e., several days).

2.2.1 Direct observation data

Observations on the behaviour of the cows were made directly in the barn by a trained student. Table 1 lists the behaviours recorded along with their descriptive definitions. Every one minute time window was assigned a label to refer to feeding, ruminating, and other activity (non-ingestive), respectively, based on the behaviour that was present during the largest proportion of that minute. Instead of removing the small number of samples of drinking behaviour (i.e., less than 2%), they were considered as feeding as per the methodology used by (Benaissa et al., 2017). As 6 hours of visual observation were available for 10 cows (Table 2), 3600 samples of observed behaviours were obtained (i.e., 3600 min).

2.2.2 Sensor data

Each cow was wearing two sensors: a RumiWatch halter and an accelerometer (Fig. 1). The RumiWatch noseband halter is intended as a measuring device for automatic health monitoring of ruminants. The system was developed by Agroscope (Ettenhausen, Switzerland) and enables automatic measurement of ruminating and feeding behaviours at 10 Hz. It incorporates a noseband pressure sensor, data logger with on-line data analysis, and evaluation software. The system also records and classifies the duration of chewing activities, and enables quantifying individual ruminating and eating chews performed by the animal (Zehner et al., 2017). On the other hand, the accelerometer was attached to the right side of the collar of each cow as shown in Fig. 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, Newcastle, UK). The orientation of the accelerometer is shown in Fig. 1. This orientation was respected for all cows. The clocks of the observer, the RumiWatch noseband, and the accelerometers were synchronized at the start of the measurement.

2.3 Processing of RumiWatch data

The output files of the RumiWatch sensor contain the classification of the considered behaviours (i.e., ruminating feeding, and other activity). Since the observations were made for each one min time interval based on the behaviour that was present during the largest proportion of that minute, the 10 Hz classification data were converted into 1-min classification summaries using MATLAB software to be comparable to the observation data (performance evaluation, section 2.5). The activity within 1 minute (i.e., 600 behaviour reports) was summarized and classified according to the most frequently occurring behaviour (either ruminating, feeding, or other activity).

2.4 Processing and classification of accelerometer data

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 1.0.0.36 (Newcastle University, UK). Then, 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 (see also Fig. 1).

Next, MATLAB software was designed to segment A_{sum} into equal time intervals of 1 min (600 samples per time interval). Together with the visual observation data (reference data), the calculated A_{sum} values (sensor data) were used as an input to the classification algorithms. In this study, two machine learning techniques were used: decision-tree (DT) and support vector machine (SVM). The DT is a fast, simple and well understood classification approach (Frank et al., 2000). The SVM technique can better handle complex classification tasks, but requires more computational power, especially in the training phase (Bishop, 2006).

2.4.1 Classification using decision-tree

A new DT algorithm was developed to distinguish between the three considered behaviours (Fig. 2). As shown in Fig. 2, the DT uses the overall dynamic body acceleration (ODBA) calculated from the A_{sum} values. The ODBA was used as it isolates the components caused directly by the movement of the animal from the static acceleration caused by the gravitation, when no movement is performed by the animal. The ODBA (equation 2) was calculated at any point in time k by smoothing $A_{sum}(k)$ using a low pass filter $\mu(k)$ (equation 3) to derive the static acceleration and then subtracting this static acceleration from the raw data (Gleiss et al., 2011):

$$ODBA(k) = |A_{sum}(k) - \mu(k)| \quad (2)$$

$$\mu(1) = A_{sum}(1);\ \mu(k) = \alpha * A_{sum}(\mathrm{k}) + (1 - \alpha) * A_{sum}(\mathrm{k} - 1)\ for\ k > 1 \quad (3)$$

α is the parameter of the low pass filter. Finally, the mean of the ODBA of each 1-min was used to build the DT algorithm (Fig. 2). In this study, α=0.15 was the best value to fit the data. A low pass filter was used instead of a running mean because it requires less computation time and both methods give similar smoothing of the vector sum (A_{sum}).

Fig. 3 shows an example of the acceleration sum vector (A_{sum}) and the corresponding ODBA values (mean each 1 min). Due to the dynamic movements of the cow's neck, the values of ODBA were the largest in the feeding. Ruminating activity includes some dynamic movements: chewing and swallowing of ruminant ingests. Especially, chewing activates the movement of the under-jaw of the cow and thus, the values of the ODBA were higher than other activity but lower than feeding. Lastly, the other activity class includes mostly samples form resting behaviour characterized by small movements of the neck. Consequently, lower ODBA values were obtained. An important advantage of using the sum vector for the classification is that the thresholds are independent of the position of the accelerometer on the collar (above, behind, or below the neck).

To determine the thresholds of the DT (Fig. 2), the nested cross-validation technique was used. This technique provides a very data efficient approach by repeatedly re-using data (Korjus et al., 2016). Since the data set contained data of 10 cows, 9 cows were used as training set and data of 1 cow was used to test the performances (leave-one-out cross-validation, Section 2.6). From the data of the 9 cows, data of 8 cows were used to find the thresholds which provide the best classification accuracy using the visual observation data of the 9th remaining cow. The mean value of 10 obtained thresholds were 0.015 g with a standard deviation of 0.0012 for the threshold 1, and 0.031 g with a standard deviation of 0.0021 for threshold 2. The coefficients of variation were 8 % and 6 % for the threshold 1 and the threshold 2, respectively. These low values indicate the general applicability of the thresholds for other cows.

2.4.2 Classification using support vector machine

To develop the SVM classification model, feature extraction was first performed for each data segment (i.e., 1-min) to transform the input data (A_{sum}) into a representation set of features (referred to as feature vectors). Feature vectors include important parameters for distinguishing between different behaviours. In this study, eight statistical features (i.e., minimum, first quartile, median, third quartile, maximum, mean, root mean square, and standard deviation) of the ODBA (i.e., the parameter used for the DT) for each 1 min time interval were derived and used as inputs for the SVM algorithm.

2.5 Effects of the sampling rate of the accelerometer

To study the effect of the sampling rate on the classification accuracy of the accelerometer, the complete 10 Hz data set exported with OmGui software was downsampled using MATLAB software at four different sampling rates (i.e., 0.5, 1, 2, and 5 Hz). Then, the same procedure as presented in Section 2.5 was repeated for each sampling rate. In order that the down sampling yields approximately the same data as sampling on the cow at lower frequencies, a uniform down sampling was used (for example for 1 Hz, we keep the first sample every 10 samples). We note here that investigating the effect of the sampling rate was not possible for RumiWatch.

2.6 Evaluation

To evaluate the classification algorithms, the precision, the sensitivity, the specificity, and the overall accuracy were used. In addition, the performance of the two sensors was evaluated in terms of the difference in ruminating and feeding times reported by the observations and the sensors. The leave-one-out cross-validation strategy was used (Arlot and Celisse, 2010). Since the data set contains 10 cows, data of 9 cows was used to train the models and find the optimal parameters (e.g., decision thresholds, Section 2.5.1) and then the models were tested by classifying the data of the tenth cow accordingly. This was repeated 10 times until data from all the cows were classified and the average precision, sensitivity and overall accuracy were considered (Section 3). The precision (Pr), the sensitivity (Se), and the specificity (Sp) are defined as (Chawla, 2005):

$$Pr = \frac{TP}{TP+FP} \tag{4}$$

$$Se = \frac{TP}{TP+FN} \tag{5}$$

$$Sp = \frac{TN}{TN+FP} \tag{6}$$

Here, TP (true positive) is the number of instances where the behaviour was correctly classified by the algorithm using observations as reference. FN (false negative) is the number of instances where the behaviour was visually observed but was incorrectly classified by the algorithm. FP (false positive) is the number of times the behaviour was incorrectly classified by the algorithm based on the reference. TN (true negative) is the number of negative samples correctly classified. The overall model accuracy is the number of TP instances of all behavioural classes divided by the total number of instances in the test set.

3. Results

3.1 Accelerometer and RumiWatch versus observation (data set 1)

The precision, sensitivity, and specificity of the considered behaviours, sensors, and classification algorithms when the highest sampling rate was used (10 Hz) are listed in Table 3 (column 10 Hz). Table 4 lists the overall accuracy for each classification approach. For the two sensors, the sensitivity of ruminating and feeding (93-94 %) was higher than other activity (86-89%). However, the precision of other activity (95-98 %) was higher than for ruminating and feeding (85 to 89 %). The specificity was similar for both sensors (95-99 %). Higher performances were obtained with the accelerometer when the SVM was used, with an overall accuracy of 93% (Table 4), compared to 91 % for RumiWatch and 90 % for the DT. Consequently, the hourly difference between the predicted and the observed ruminating time (in min/h) was less than 1 min/h (1.5% of the observed time) for the SVM and less than 2 min/h (2.8%) for both DT and the RumiWatch. For the difference in feeding time, 1.3 min/h (2.4%) was obtained with the SVM compared to 2.5 min/h (4.3%) and 2.4 (4.1%) min/h for both RumiWatch and DT, respectively (Table 5).

3.2 Accelerometer versus RumiWatch (data set 2)

Similar to the data set 1, the difference in ruminating time was lower than the difference in feeding time (about 1 min/h). However, for both ruminating and feeding, the obtained differences with data set 2 were slightly higher than data set 1 (Table 5). When looking into the classification technique used with the accelerometer, the SVM was closer to the RumiWatch (1.3 min/h for ruminating and 2.1 min/h for feeding) than the DT (2.6 min/h for ruminating and 3.2 min/h for feeding).

3.3 Effect of sampling rate

The classification performances of the accelerometer data decreased for lower sampling rates (Table 3). Ruminating was influenced most by the decrease of the sampling rate especially for the DT algorithm and with sampling rates below 1 Hz. However, other activity was less influenced by the decrease of the sampling rate, especially the precision, which varied from 96% at 10 Hz to 94 % at

0.5 Hz. Overall, the classification accuracy was still over 82% for both algorithm when 0.5 Hz was used (Table 4).

4. Discussion

The present study investigated the use of a neck-mounted accelerometer for monitoring ingestive-related cow behaviours based on a simple DT algorithm. The classification performance of the DT was compared to SVM (applied to neck-mounted accelerometer data) and RumiWatch noseband sensor. In general, the SVM presented the highest accuracy measures compared to the DT and RumiWatch, which presented comparable results (Table 4). The classification using SVM considers more features (i.e., 16) than the DT (only 1), leading to a higher classification accuracy. Although the SVM algorithm performed better than the DT (Alpaydın, 2014), it is more suitable for complex classification tasks and it requires more computation capabilities than DT (Douglas et al., 2011), especially in the training phase. This makes it difficult to be implemented locally on the node attached to the cow's collar. Therefore, the raw data should be transmitted to a processing centre before classification, which requires a broadband and power-hungry wireless connection and limits the battery lifetime of the sensors. The sensitivity of the DT was 93 % for feeding and 92 % for ruminating and matched the performance of the RumiWatch sensor. Similar results were obtained in Zehner et al., (2017), where the RumiWatch noseband sensor classified ruminating and eating behaviours with an accuracy of 94 % and 92 %, respectively.

When comparing the individual behaviours, ruminating and feeding were classified with higher sensitivity than other activity. The neck of the cow shows high activity during feeding, which explains why neck-mounted accelerometer data allow this behaviour to be distinguished easily from the other behaviours (Martiskainen et al., 2009a). Also, the other activity class includes samples from walking and brushing. These two activities have patterns similar to feeding. The values of the specificity of the three behaviours were similar to those obtained in Zehner et al. (2017). The relevance of these results is clearer when looking into the difference in ruminating and feeding time (Table 5). Based on the daily time budget of lactating dairy cows in free-stall barns presented in Grant (2007), a lactating cow spends 7 to 10 hours ruminating. This means that the daily error of the DT algorithm ranges from 12 to 17 min (1.7 min/h). This is less than 2 % of the daily ruminating time. Similarly, the error in feeding time was 2.6 min/h for the DT. This means a daily error between 8 and 13 min, which is less than 6 % of the daily eating time (the daily eating time of a lactating cow ranges from 3 to 5 hours, Grant, 2007). Thus, the proposed DT algorithm can accurately (95 %) detect the daily changes (behaviours) in feeding and ruminating time. When looking into the applications of the DT on the dairy farms, it is reported by Norring et al. (2014) that lame cows spend less time feeding per day (e.g., 101 ± 4 min/d for lameness score 3, i.e., moderately lame). This daily change is higher (7 times) than the daily error in feeding time presented by the DT (8-13 min/d). In addition, the daily error of ruminating time obtained by the DT (12-17 min) is 4-6 times lower than the daily deviation of ruminating time around calving (63 min, Schirmann et al., 2013) and oestrus (68 min, Reith et al., 2014). Similarly, the daily error of feeding time (8-13 min) is 6-8 times lower compared to the daily deviation of feeding time before calving (66 min, Schirmann et al., 2013). Consequently, the DT could be implemented for the detection of lameness, calving, and oestrus, which would enhance the health and the welfare of the cows as well as the productivity of the dairy farm.

The last part of this work was the investigation of the sampling rate effect on the classification performance of the accelerometer data. As expected, the accuracy decreased for lower sampling rates for both algorithms (DT and SVM). However, it was still over 82% when 0.5 Hz was used. Such a considerable reduction in sampling rate could save the sensor’s power and minimise the storage load of the monitoring system (a reduction of 95 %). The decrease in the ability of accelerometers to identify behaviour patterns when the sampling rate decreases was also noticed when monitoring goat behaviours (Moreau et al., 2009). To overcome this decrease, an appropriate selection of the classification algorithm could enhance the accuracy when lower sampling rates are used. Ruminating behaviour was influenced most by the decrease of the sampling rate especially for the DT algorithm and with sampling rates below 1 Hz. The use of a lower sampling rate less than 1 Hz leads to misclassification for ruminating, not because of down sampling, but due to the jaw movement of the cow, which moves faster than 1 time per second during ruminating (63 to 80 times per min, Zehner et al. (2017)). Therefore the accelerometer is unable to detect these movements at 0.5 Hz or slower.

The presented classification system (accelerometer-DT and accelerometer-SVM) cannot report the number of eating bites, chews, and ruminating chews, which could be used to estimate the feed intake (Zehner et al., 2012). This is an important limitation in comparison to RumiWatch noseband sensor (Ruuska et al., 2016). Although, the present results showed good classification of ruminating and feeding, more research is required to address other issues. For example, the observation time per cow (i.e., 6 hours) was not sufficient to collect enough data for some behaviours such as drinking. This behaviour could be classified as a separate behavioural class when more samples become available. Also, only feeding time was measured and not the feed intake. The cows may change food intake by changing rate of intake, which cannot be detected by our current methodology. Therfore the link between food intake and time eating needs further investigation. Hence, a closer analysis of the feed intake appears to be difficult when using the current accelerometer system. The selection of relevant features should be addressed for the SVM algorithm in order to reduce the number of features used for the classification. This would lower its computation time as well as enhance its performances. Finally, data from other herds would be needed to validate the findings of this research.

5. Conclusions

This study confirmed that a simple DT algorithm applied to data from a neck-mounted accelerometer was effective for classifying feeding and ruminating behaviours of dairy cows with performances comparable to RumiWatch noseband sensor. The calculation procedure and the thresholds of the DT provided in this paper could be useful for rapid and real-time implementations. The methods proposed allow a possible reduction of the sampling rate, but not lower than 1 Hz. Future work will consist of expanding this research to other herds, additional behaviours (drinking, walking), and different environments (e.g., pasture), in order to broaden the possible applications of the monitoring system. This will enable the determination of relevant information about the cows' behavioural patterns (e.g., daily changes of feeding time, ruminating time). Such information could offer new potential technologies for the automated detection of health, productivity, and welfare problems in dairy cows (e.g., lameness, mastitis, calving).

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8. Figure captions

Fig. 1. Cow with RumiWatch noseband and accelerometers sensors. The orientation of the accelerometer is indicated by the arrows.

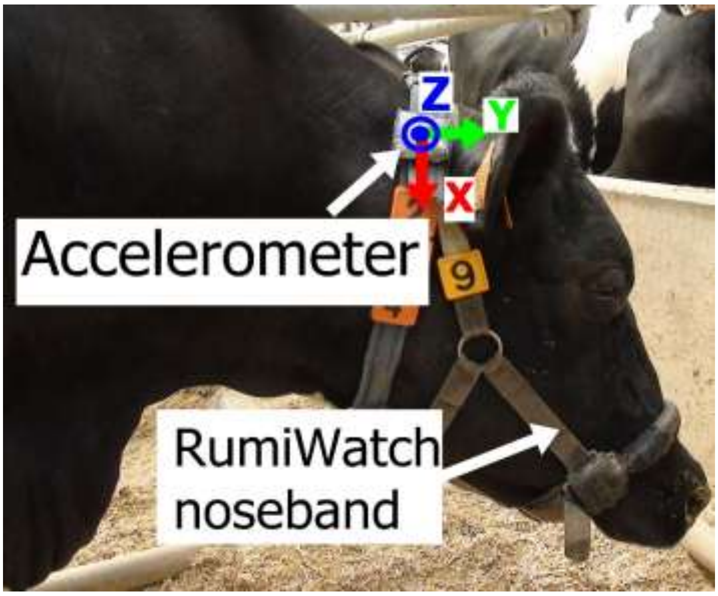


Fig. 2. Classification approach using decision tree algorithm. The scheme was designed to be as simple as possible to be implemented on the on-cow node. The decision rule uses one parameter (mean value of the ODBA) and two thresholds to distinguish between feeding, ruminating, and other activity.

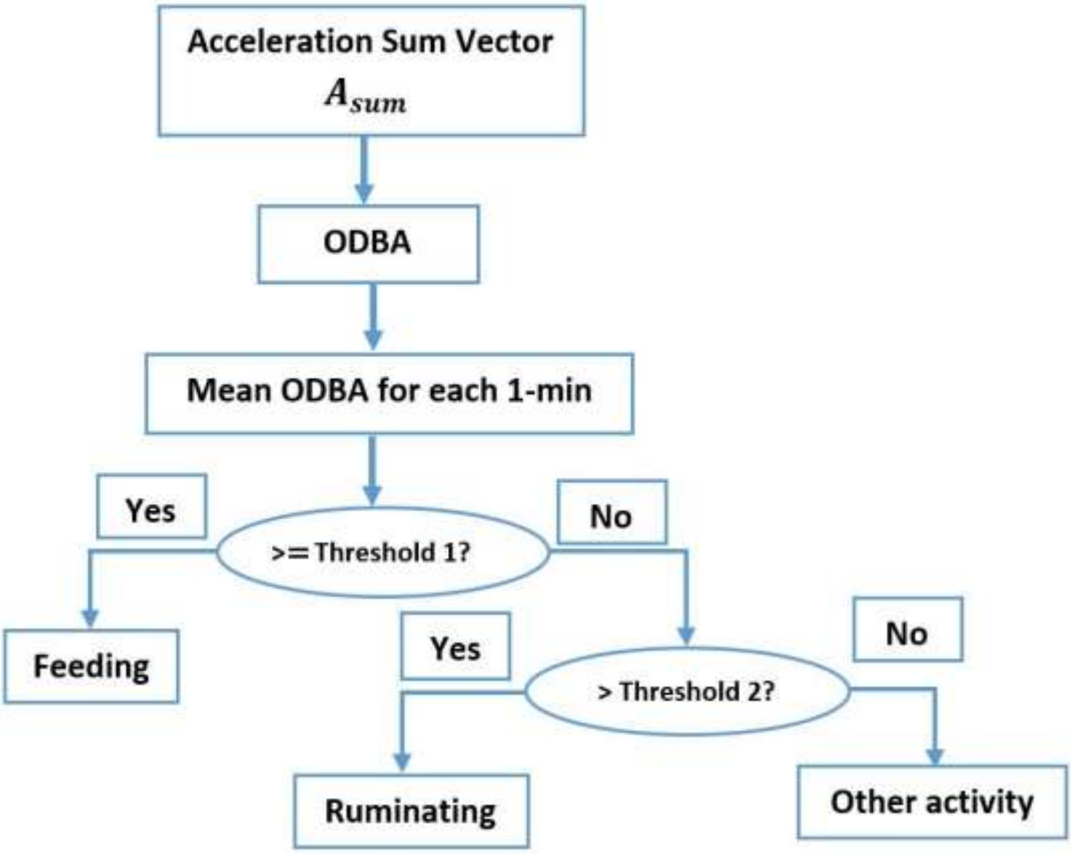
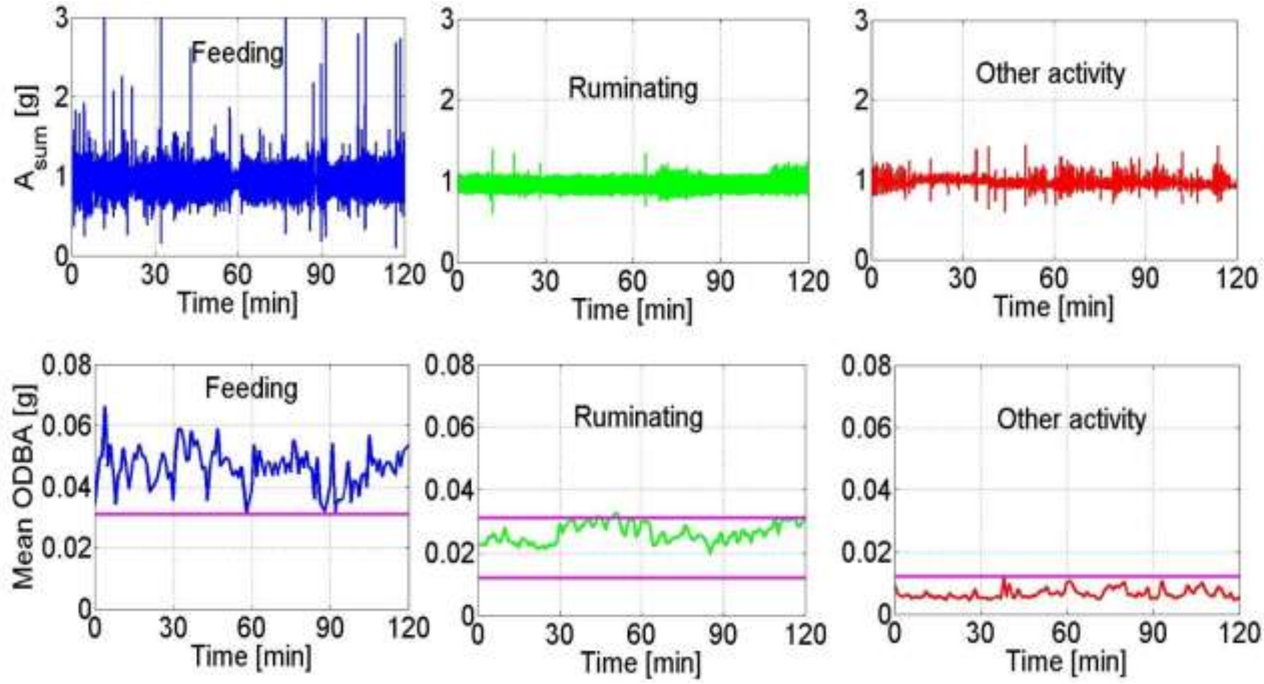


Fig. 3. Example of the acceleration sum vector (A_{sum}) from the neck-mounted accelerometer and the coresponding ODBA values (mean each 1 min) for the considered behaviours. The mean value of the ODBA was used as a decision parameter for the decision tree algorithm (The thresholds 0.012 and 0.031 are indicated with pink lines).



9. Table captions

Table 1. Description of the observed behaviours. The behaviours are grouped in three behavioural classes (i.e., feeding, ruminating, other activity) (Zehner et al., 2017).

Observed Behaviours	**Description**	**Number of samples***
Feeding	Eating : Intake, chewing, and swallowing of feed Drinking: Putting mouth in water bowl and swallowing water	932 (26 %)
Ruminating	Chewing and swallowing of a ruminating bolus	1104 (31 %)
Other activity	Non-ingestive related activities	1564 (43 %)
Total (SUM)		3600 (100 %)

* Number of 1 min time intervals for each observed behaviour

Table 2. The number of samples observed for each cow and each behaviour.

	Cow										Total
Activity	1	2	3	4	5	6	7	8	9	10	
Feeding	73	57	93	133	121	110	94	68	93	90	932
Ruminating	114	119	83	89	103	129	125	101	126	115	1104
Other activity	173	184	184	138	136	121	141	191	141	155	1564
Total	360	360	360	360	360	360	360	360	360	360	3600

Table 3. Precision (Pr), sensitivity (Se) and specificity (Sp) [%] for each behavioural class and classification approach using different sampling rates. DT: decision-tree, SVM: support vector machine. Values in bold indicate the behaviour class for which the highest values were reached for each sensor.

			10 Hz			5 Hz			2 Hz			1 Hz			0.5 Hz		
			Pr	Se	Sp	Pr	Se	Sp	Pr	Se	Sp	Pr	Se	Sp	Pr	Se	Sp
Accelerometer	DT	Other activity	**96**	86	**99**	**96**	86	**98**	**95**	83	**98**	**93**	82	**97**	**94**	78	**97**
		Ruminating	86	92	95	82	**93**	92	79	**93**	90	76	88	91	70	86	88
		Feeding	89	**93**	95	87	92	94	87	91	94	84	**93**	92	83	**90**	92
	SVM	Other activity	**98**	89	**97**	**95**	87	94	**93**	86	94	**90**	83	91	87	85	88
		Ruminating	88	**92**	96	86	**94**	**96**	85	**94**	**95**	88	**92**	**96**	**92**	74	87
		Feeding	92	85	95	89	88	**96**	87	87	**95**	87	90	**96**	88	**96**	**94**
RumiWatch		Other activity	**95**	87	**98**												
		Ruminating	85	**94**	95												
		Feeding	88	93	95												

Table 4. Overall accuracy for each classification approach using different sampling rates. DT: decision-tree, SVM: support vector machine.

	10 Hz	5 Hz	2 Hz	1 Hz	0.5 Hz
Accelerometer: DT	90	88	87	85	82
Accelerometer: SVM	93	92	90	89	86
RumiWatch	91				

Table 5. Difference in ruminating and feeding times (in min/hour and in % of the observed time) between observation and sensors (data set 1) and between accelerometer and RumiWatch (data set 2) using a sampling rate of 10 Hz. DT: decision-tree, SVM: support vector machine, Acc: accelerometer.

		Ruminating time		Feeding time	
		Difference in [min/h] (mean±SD)	Difference in [%]	Difference in [min/h] (mean±SD)	Difference in [%]
Data set 1	Acc (DT) Vs observation	1.7±0.8	2.8	2.6±1.2	4.3
	Acc (SVM) Vs observation	0.9±1.1	1.5	1.3±1.6	2.1
	RumiWatch Vs observation	1.6±0.9	2.6	2.5±1.7	4.1
Data set 2	RumiWatch Vs Acc (DT)	2.6±2.3	4.3	3.2±2.0	5.3
	RumiWatch Vs Acc (SVM)	1.3±1.1	2.1	2.1±1.7	3.5