Evaluation of a sensor-based system for monitoring rumination in dairy cows with access to pasture

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Abstract

Monitoring the health and welfare of animals is time consuming, especially on pasture. Monitoring systems can assist the farmer in detecting the oestrous and emerging health disorders by continuously predicting the animal behaviour and its changes. Rumination behaviour has proven to be a useful indicator. As most of the monitoring systems available on the market were either developed for the stable or for pasture and fail to detect the behaviour reliably in the other location, our goal was the development of a monitoring system for dairy cows kept on pasture as well as in the stable. As a first step, a model for the prediction of rumination behaviour was developed and evaluated. Up to eleven cows on three different farms were equipped with the collar-based prototype of the monitoring system. The system contained a 3D accelerometer and a gyroscope, both collecting data at 10 Hz. Ground Truth data were collected by recording the animals with cameras and labelling the video data based on an ethogram. The data from three animals (30.4 h) on farm 1 were used for training the model. Random Forest and a window size of 5 s without overlap proved to achieve the highest accuracy compared to other classifiers and window sizes. An orientation-independent feature set with 26 features was chosen. The model was evaluated on data from the remaining animals (184.8 h). The output of the model and Ground Truth were compared second by second. Overall accuracy of the model in detecting rumination behaviour was 97.4 %. Lying without rumination was the behaviour confused the most with rumination by the model. From individual rumination bouts, 97.1 % were successfully predicted by the model. The duration of rumination bouts did not differ ($p = 0.70$) between model output and video observation. Compared to other models for the prediction of rumination behaviour, our model achieved high accuracies both on pasture and in the stable.

Keywords: PLF, accelerometer, gyroscope, grazing, behaviour recognition

1. Introduction

Rumination behaviour increases the saliva production which buffers the acids produced in the rumen within the bacterial carbohydrate decomposition. Besides, masticating the feed increases the surface available for bacterial decomposition in the rumen. Eventually, rumination enables (dairy) cows to use fibrous plant material as energy source. Healthy dairy cows show approximately 7 to 8 h of rumination behaviour per day depending, e.g., on the husbandry system (Gregorini et al. 2013), the size of the animal (Bae et al. 1983), the parity (Miguel-Pacheco et al. 2014), the phase of lactation (Gáspárdy et al. 2014) and the milk yield (Soriani et al. 2013). Rumination behaviour is shown in 13 to 15 bouts per day (Dado and Allen 1994).

Rumination behaviour is a useful indicator for the health and welfare status of dairy cows. Deviations in daily rumination time and the frequency and the duration of rumination bouts provide valuable information for the detection of the oestrous as well as for the identification of emerging health disorders or health challenges. Abeni and Galli (2017) found a decrease in rumination time, especially during the day, in cows exposed to heat stress. Also on the day prior to calving and on the calving day itself, dairy cows show a reduced rumination time (Clark et al. 2015) making it a useful indicator for the detection of calving. Mayo et al. (2019) and Minegishi et al. (2019) found a reduction of rumination time on the day of oestrous, confirming that by assessing rumination behaviour, oestrous can be detected. Besides, various health disorders lead to decreased rumination times, e.g. subclinical ketosis (Kaufman et al. 2016), lameness (Miguel-Pacheco et al. 2014), mastitis (Stangaferro et al. 2016b) and metritis (Stangaferro et al. 2016a).

To detect changes in rumination time in dairy cows, rumination behaviour must be recorded continuously. The automated and continuous measurement of rumination time can be realized with monitoring systems. With different sensors, e.g. accelerometers, pressure sensors or microphones, those systems detect movements of the head, neck, jaw, or ear or sounds associated with movements of the jaw. By training and applying suitable machine learning models on the sensor data, behavioural patterns like rumination can be predicted automatically. For the stable, various systems have proven to reliably detect rumination behaviour. Martiskainen et al. (2009) developed a model that predicted rumination behaviour with high accuracy in dairy cows kept in a barn. Borchers et al. (2016) evaluated the performance of an accelerometer sensor attached to the ear and found high correlations between visual observation and the system output for rumination behaviour. A collar-based monitoring system was assessed by Grinter et al. (2019) and Werner et al. (2018) evaluated the performance of a halter containing a pressure sensor. Both systems performed well in predicting rumination behaviour in dairy cows. Hamilton et al. (2019) successfully developed a model for the automated detection of rumination periods with an accelerometer integrated into a rumen bolus. On pasture, on the other hand, most of the systems developed for the stable perform weakly (Ambriz-Vilchis et al. 2015; Elischer et al. 2013). González et al. (2015) developed an algorithm for the detection of rumination behaviour in steers kept on pasture with a collar-based system and achieved high accuracies in the evaluation of the algorithm. An algorithm for the automated prediction of rumination behaviour from sound data collected with a microphone was developed and evaluated by Chelotti et al. (2020). The algorithm detected rumination behaviour as well as individual rumination bouts with high accuracies. Both studies focused on behaviour data from pasture and did not include data from the stable. Kononoff et al. (2002) on the other hand evaluated the performance of a noseband sensor which was developed for pasture on dairy cows in a barn and found significant differences in the rumination time predicted by the system compared to visual observation.

As the available monitoring systems developed for the detection of rumination behaviour in dairy cows were either developed for the stable or for pasture, exclusively, and fail to reliably predict rumination in the other location, the goal of the presented study was to develop a model for the automated detection of rumination behaviour in dairy cows kept on pasture as well as in the stable.

2. Materials and Methods

2.1. Animals and farm management

All performed procedures followed the EU directive 2010/63/EU and the German Welfare Act. Data collection methods were previously described in Schmeling et al. (2021). Data collection was conducted on three different dairy farms in Upper Bavaria, Germany. On all farms, calving was seasonal, the herds consisted of dairy cows mainly from the Simmental breed and the animals had access to pasture during the summer months. All cows were kept in or had access to a free stall barn. On farm 1, access to the barn was limited to two hours around each milking. Permanent access to the barn was granted during the day on farm 2, while during the night, the cows were kept on a smaller pasture without access to the barn. As observations on farm 3 were made during winter, the cows were kept in the barn all day long without access to pasture. Details on the three farms and their management can be found in Table 1.

Two observation rounds of two consecutive days each were conducted on farm 1. On farm 2 and 3, one observation round of three and four consecutive days, respectively, were performed. For the trials, animals in the second to fifth lactation were chosen randomly from each herd. Only cows free from clinical symptoms of any kind were included in the trial. Details on the selected cows can be found in Table 2.

Table 1 – Details on farms and farm management.

Farm	No. of cows in the herd	Size of pasture [ha]	Type of milking parlour	Milking times	Feed (feeding times)	Type of cubicles	No. of cubicles
1	40	17	herringbone	6 am / 5 pm	-[4]	deep, straw-bedded	40
2	34	12[1] / 3[2]	herringbone	7 am / 4 pm	-[4]	deep, litter	34
3	52	-[3]	tandem	6 am / 6 pm	TMR (10 am / 6 pm)	high, rubber mattresses	48

[1]access during the day, [2]access during the night, [3]observations made during winter, [4]main feed derived from pasture

Table 2 – Details on the dairy cows included in the trials.

Farm	No. of round	No. of chosen animals	Parity (mean ± sd)	DIM[1] (mean ± sd)
1	1	7	3.1 ± 0.7	233 ± 30
	2	8	3.5 ± 1.2	285 ± 40
2	1	8	4.0 ± 1.2	101 ± 46
3	1	11	4.0 ± 0.9	273 ± 16

[1]Days in milk (DIM) on the first day of the trial

2.2. Behaviour data collection

On all three farms, the selected animals were equipped with the prototype of a monitoring system (Blaupunkt Telematics GmbH, Hildesheim, Germany) attached to a collar. The system contained a three-dimensional accelerometer and a triaxial gyroscope (BNO055, Bosch Sensortec GmbH, Reutlingen, Germany). Data sampling frequency was set to 10 Hz. Raw data was stored on an integrated SD memory card (32 GB; SanDisk; Western Digital Deutschland, GmbH, Aschheim, Germany) and downloaded after each round.

In parallel with the sensor data, behaviour data were collected. Therefore, the selected animals were observed with five (pasture) to seven (barn) cameras (GoPro HERO5, GoPro, Inc., San Mateo, USA) for 5 to 8 h per day. After the observation rounds, the video data were analysed. The behaviour of each cow was classified at every second based on an ethogram. Video analysis was conducted by one observer only, avoiding errors between observers. Rumination behaviour was defined as the time between the regurgitation of the first and the re-swallowing of the last bolus of a rumination bout. A gap of 60 s in between two boli separated two rumination bouts based on the criteria used by Werner et al. (2018) and the findings from Kononoff et al. (2002). Besides rumination behaviour, lying, grazing, walking, standing and additional behaviours like chewing, social, comfort and explorative behaviour were labelled (Schmeling et al. 2019). The data from all animals on all days from farm 1, all animals on one day from farm 2 and three animals on one day from farm 3 were analysed in detail with rumination behaviour being labelled.

2.3. Model development

The data sets consisting of sensor data from the accelerometer and the gyroscope and the Ground Truth data (= behaviour data) derived from the video observation served as basis for the development of the machine learning model for rumination behaviour. Data from two animals from farm 1 from the first round and one animal from farm 1 from the second round were chosen for the development. From the chosen data, 20 % were used for the training of the model and 80 % served as the basis for the evaluation within the model development. The goal was to develop a binary model that is able to distinguish between rumination and non-rumination behaviour. Lying without ruminating, grazing, standing, and walking were considered as non-rumination behaviour. Each behavioural pattern shared 25 % of the training data set. Down-sampling from 10 to 9, 7, 5 and 3 Hz was examined by calculating the mean. Different algorithms (Random Forest, Decision Tree, Support Vector Machine and Naïve Bayes), window sizes (5, 6, 8, 10 and 12 s) and strides (50 %, 75 %, 100 %) were assessed. Various features were applied to the magnitude of the accelerometer and the gyroscope data and given to the classifiers. Different combinations of model characteristics were regarded to find the best combination for a successful prediction of rumination behaviour. As the output of the model was noisy, a filter was applied to the model data. All rumination and non-rumination sequences with a duration of <60 s were disregarded and added to the behaviour classified in the preceding sequence.

2.4. Model evaluation and statistical analysis

The model output and the Ground Truth data were compared second by second. Seconds of rumination behaviour correctly identified as rumination were considered as true positive (TP). Seconds correctly predicted as non-rumination behaviour were considered as true negative (TN). Seconds of rumination in Ground Truth that were predicted as non-rumination behaviour by the model were defined as false negative (FN) and seconds of non-rumination falsely predicted as rumination behaviour as false positive (FP). These values were used to calculate the sensitivity, specificity, and accuracy of the model in predicting rumination behaviour. Regarding duration, only rumination bouts that were observed without an interruption of >60 s in Ground Truth were compared to the duration predicted by the model. Only beginnings and endings of bouts preceded or followed by 60 s of non-rumination behaviour in Ground Truth (= threshold that divided two bouts from each other) were compared between Ground Truth and model output.

The statistical analysis was performed in RStudio 1.3 (RStudio, Inc., Boston, USA). Data was tested for normality using Shapiro-Wilk test. For normally distributed data average and standard deviation is given as $\bar{x}$ ± sd. For data that was not normally distributed the median is given. The difference in rumination time and the duration of rumination bouts between Ground Truth and model output, as well as the difference between rumination time in the stable and on pasture and the rumination time during the day and during the night were assessed with a two-sample t-test. P-values <0.05 were considered as significant.

3. Results and Discussion

3.1. Collected data

With the chosen methods, 1516.0 h of sensor data were collected. From the videos, 219.3 h of corresponding Ground Truth data where rumination behaviour was labelled were collected. This share was available for the development and the evaluation of the model for the prediction of rumination behaviour in dairy cows. The final model was applied to all sensor data collected for the assessment of rumination time. One animal was excluded because it showed oestrous symptoms within the observation round.

A share of 14.1 %, equalling 30.4 h of data sets were chosen for the model building and the remaining 184.8 h were used for evaluation of the model. While for the development of the model all data were derived from the pasture, the data for the evaluation was divided among pasture (120.1 h) and stable (64.7 h). The available time both for model development and evaluation exceeded the one in the study of González et al. (2015) where 18 h of continuous behaviour data was used for the development of the model and 25 h were collected for the evaluation for the model. Borchers et al. (2016) evaluated an ear tag-based sensor in detecting rumination behaviour and had a similar amount of time (48 animals, 4 h, equalling 192 h) available for the evaluation.

In total, 105 rumination bouts were observed in Ground Truth. For 46 bouts the duration between Ground Truth and model output could be compared. The beginning of 82 bouts and the ending of 72 bouts was included in the evaluation and compared between Ground Truth and model output.

3.2. Developed model

Down-sampling did not bring any benefit and the sampling frequency was left at 10 Hz. The same sampling frequency was used in the study of Martiskainen et al. (2009) and González et al. (2015) for the development of a rumination model. Random Forest proved to be the most accurate algorithm for the prediction of rumination behaviour compared to other classifiers (Decision Tree, Support Vector Machine and Naïve Bayes) in our study. In contrast, Support Vector Machine (Hamilton et al. 2019; Martiskainen et al. 2009) and Decision Tree (González et al. 2015) were used but not compared with other algorithms in other studies. A window size of 5 s without overlap and an orientation-independent feature set with 26 features achieved the highest accuracy. A window size of 10 s without overlap was used by González et al. (2015) who showed that longer windows result in lower accuracies. An orientation-independent feature set ensures high accuracies regardless of sensor shifting caused by movement of the animals (Kamminga et al. 2018). By applying a filter of 60 s the model data was smoothed. As non-rumination bout lasted less than 60 s in Ground Truth, no information was lost by deploying the filter. In contrast, only with the filter individual lying bouts could be identified in the model output.

3.3. Performance of the model and rumination behaviour

In total, the developed model predicted rumination behaviour with a sensitivity of 92.6 %, a specificity of 99.3 % and an accuracy of 97.4 %. Performance on pasture (sensitivity: 91.7 %, specificity: 99.7 %, accuracy: 97.6 %) was slightly higher than in the stable (94.6 %, 98.4 %, 97.0 %). In total, variation between animals was small (min. accuracy: 94.9 % vs. max. accuracy: 99.1 %). The accuracy and sensitivity of our model exceeded the performance values of a model developed by Martiskainen et al. (2009) for dairy cows kept in a barn. Lower performance was achieved by the model developed by Hamilton et al. (2019). The model developed by González et al. (2015) for steers on pasture reached similar specificity (99.4 %) but a higher sensitivity (98.4 %). In this study, the development and the evaluation of the model were limited to data from pasture. Ambriz-Vilchis et al. (2015) evaluated a system for the monitoring of rumination behaviour in dairy cows both in the barn and on pasture. For the barn, they found a high correlation between video and visual observation and the system output for rumination time but on pasture correlation was poor. This finding is supported by the results of Elischer et al. (2013) who evaluated a collar-based system on a mixed data set from the barn and the pasture and found major differences in rumination time recorded by the system in comparison with visual observation. In contrast to other studies, our model performed well in detecting rumination behaviour in dairy cows kept in a barn as well as on pasture.

The FN time (= time when model predicted non-rumination behaviour, but the animals were showing rumination behaviour in Ground Truth) amounted up to 3.8 h (2.1 %). The FP time (= time when model predicted rumination behaviour, but animals were not ruminating in Ground Truth) on the other hand totalled only 1.0 h (0.5 %) of the observed time. The behavioural patterns that were confused the most with rumination by the model were lying without ruminating (46.2 %), standing without additional behaviour (22.8 %) and standing with additional behaviour like feeding, drinking, or chewing (18.7 %). These findings correspond to the results obtained by Martiskainen et al. (2009). Their model confused rumination behaviour with lying and standing the most as well.

Rumination time per animal per observation day was slightly overestimated by the model but did not differ significantly between Ground Truth and model output (1.7 vs. 1.6 h; $p = 0.70$; see Figure 1). In contrast, the system evaluated by Grinter et al. (2019) underestimated rumination time compared to visual observation. In our study, the share of rumination time of the total observed time in Ground Truth and model output was similar (29.8 vs. 28.3 %).

The model correctly detected 105 out of 109 rumination bouts, equalling 97.1 %. Of the 105 bouts, two (1.9 %) were merged to one and six (5.7 %) were divided into two or three bouts by the model. The model missed three rumination bouts that were observed in Ground Truth. More rumination bouts were not recognized, recognized too much, merged or divided by different models evaluated by Chelotti et al. (2020) for the automated detection of rumination behaviour from sound data derived from cows on pasture.

There was no significant difference between the duration of rumination bouts in the model output compared to Ground Truth (33.4 vs. 34.6 min.; $p = 0.70$; see Figure 2). Variation of rumination bout duration was large (Ground Truth min.: 6.7 min, Ground Truth max: 75.6 min; model output min: 5.7 min, model output max: 74.6 min). Dado and Allen (1994) found a slightly higher rumination bout duration (36.0 min) but variation was larger. In a study conducted by Kononoff et al. (2002), high agreement was found between the duration of rumination bouts predicted by a noseband-based system with visual observation as well, but the difference (+1.9 min) was slightly higher than in our study (+1.2 min). As our observations were limited to daytime, rumination bout duration could vary when night-time is considered as well.

From the compared beginnings of the rumination bouts, 29.3 % were detected ± 5 s from the beginning in Ground Truth. Most of the rumination bout beginnings were detected too late (56.1 %), a few beginnings were detected too early (14.6 %). Median difference in the beginning detected by the model compared to the beginning in Ground Truth was 53 s. The model detected the endings of 34.1 % of the rumination bouts within ± 5 s from the ending in Ground Truth. Part of the endings was detected too early (23.2 %) and part too late (30.5 %). Median time deviation between the endings of rumination bouts was -1 s. To our knowledge there is no study evaluating the detection of rumination bout beginnings and endings with a sensor-based system.

By applying the model to the entire sensor data (1516.0 h), the rumination behaviour could be assessed. In general, significantly more time per day was spent ruminating in the stable (farm 3) than by cows with access to pasture (farm 1 and 2; 8.2 vs. 7.1 h; $p < 0.05$). In a study conducted by Beer et al. (2016), higher rumination times were found for German Holstein cows kept in a stable. Similar rumination times were found in the study of Gregorini et al. (2012) for cows in the stable and cows that spent 24 h on pasture. On pasture, significantly more time was spent ruminating during the night (6 pm to 6 am) compared to the day (6 am to 6 pm; 4.2 vs. 3.2 h; $p < 0.05$). This finding is supported by the results of Gregorini et al. (2012) where cows showed more rumination time during the night than during the day as well. More time was spent ruminating during the day than during the night in the stable as well, but the difference was not significant (4.3 vs. 3.9 h; $p = 0.07$).

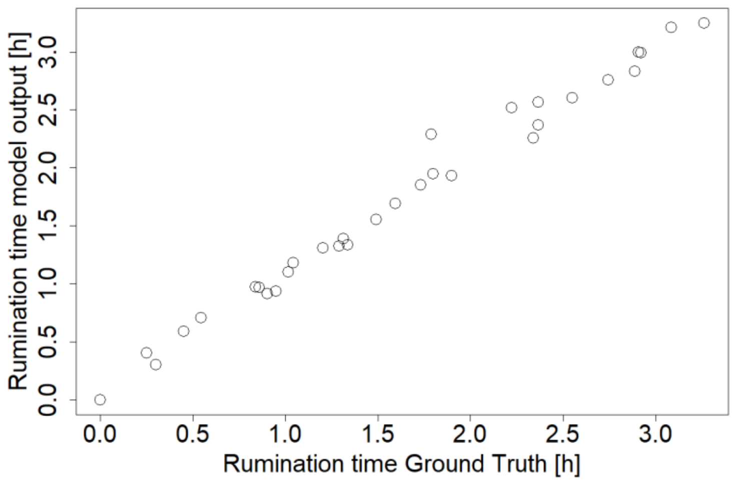

Figure 1 – Comparison of rumination time per animal and observation day (6-8 hours of total time observed per day) between Ground Truth and model output.

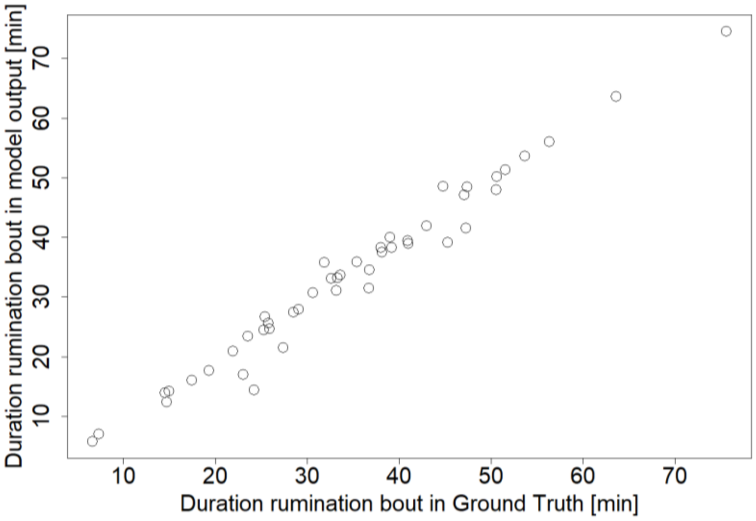

Figure 2 – Comparison of rumination bout duration between Ground Truth and model output

4. Conclusions

To summarize, the model developed for the collar-based prototype monitoring system predicted rumination behaviour in dairy cows with high accuracy. No significant differences in rumination time were found compared to rumination time recorded by video analysis. Also, the model was able to accurately detect individual rumination bouts and their duration. The good performance of the rumination model enables the sensor system to reliably detect rumination behaviour and changes in rumination behaviour caused, e.g., by oestrus, emerging health disorders, calving, or health challenges like heat load. Unlike previously assessed systems, the model was tested both on data from the stable and pasture and performed similarly well in both locations. Therefore, it is applicable on farms with either or both husbandry systems.

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