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Classification of cattle behaviour in a forested habitat using data from activity sensors

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Preface

This thesis marks the termination of my master's degree in Sustainable Agriculture at Hedmark University of Applied Sciences. The idea and work of this thesis started in spring 2015, by planning and preperation for field work. During the summer of 2015, many days were spent in the deep forest of Stange and Romedal. Much of the time was used looking for cattle or being frustrated when we did not find them. When cattle was found, hours were spent observing their behaviour, which at times resulted in hearing the sound of cowbells, wheather cattle was nearby or not. However, I would never take back the experience of spending time in that beautiful scenery, gazing at the fascinating behaviours performed by cattle. I found the work of this thesis to be interesting and, due to little knowledge in the beginning, the process of treating data and writing made me learn a lot in relatively short time.

My thesis would most certainly not be the same without the help of my supporters. I would like to thank my supervisor Morten Tofastrud for including me in his project, suggesting this topic and for all help during the process of writing. Another thank you goes to the farmers who participated in the project and let us use their cattle, making this study possible. For good help and support in field observations, I want to thank Camilla Rung and Ulvi Selgis. In addition I want to thank Barbara Zimmerman and Olivier Devineau at Evenstad for technical and statistical advice during the process.

Finally, I would like to thank my friends and family for their support.

Blæstad, 03.05.2016

Hilde Hegnes

Abstract

GPS collars with activity sensors can be used to record movement and activity of free-ranging cattle. In forests grazed by cattle, resources are utilized where they exist, an important consideration for sustainable land use. Since animal behaviour can indicate state of health and nutrient uptake, monitoring grazing activity and classifying cattle behaviour based on collar recordings might contribute to provide sufficient welfare management. Several statistical methods have previously been trialled to classify behaviours using data from activity sensors, however, no method is standardised. This study mainly aims to use classification tree models to classify binary activity and grazing behaviour.

17 cattle on pasture in the forest of Stange and Romedal common land were equipped with dual-axis activity sensor collars and behaviour was observed during summer months of 2015, resulting in 1105 sequences of observed behaviour. Data from observations were used for testing accuracy of activity sensors to classify behaviour. Classification of binary activity (low vs. high) was 89.3%. When adding grazing as a category, classification was 80.8%. This suggests classification to be more difficult when adding more behaviour categories to the model and some behaviours are correlated to the same activity level. In addition to activity data from the collars, distance of movement between sequences was chosen by the model as an important variable to classify behaviour.

Keywords: cattle behaviour; GPS collars; activity sensors; accelerometer; dual-axis sensor; classification tree; grazing; pasture; free-ranging cattle

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1. Introduction

The Norwegian government intends to facilitate diversified agriculture throughout the country and emphasizes the use of national resources where they exist, such as forage and pasture, the latter is considered a sustainable way of utilizing land area (Landbruks-og matdepartementet, 2011). This national goal benefits from new technology that gradually allows researchers to step aside from testing in highly controlled conditions and to find answers to questions about behaviour in the animals' natural environment, even over large distances (Wilmers et al., 2015). In a critical review of 22 different studies, comprising a total of 40 behaviours of cattle on pasture, Kilgour (2012) highlighted three main categories taking up 90-95 % of the daily activity; most common is grazing, followed by ruminating and resting. The time budget of cattle activity varies: grazing is mostly performed during hours of daylight, ranging from 4.5 to 9.3 hours. During daylight, rumination, resting and walking is performed for 1.4-6.9 hours, 2-3.5 hours and 0.2-2.9 hours, respectfully.

Positioning technology, the global positioning system (GPS) in particular, has become commonly used for monitoring behaviour, movement and pasture use of cattle (Turner, Udal, Larson, & Shearer, 2000). Ganskopp (2001) concluded in his study that movement based on GPS and observed behaviour did not correlate directly, however his study did not include any activity recording besides the movement itself. Accelerometer activity sensors are used to record activity of cattle (González, Bishop-Hurley, Handcock, & Crossman, 2015; Guo et al., 2009; Martiskainen et al., 2009; Pastell, Tiusanen, Hakojärvi, & Hänninen, 2009; Robért, White, Renter, & Larson, 2011; Watanabe, Sakanoue, Kawamura, & Kozakai, 2008; White et al., 2008). GPS collars with accelerometer activity sensors are combining the technology of position and activity recording, making it possible to study animal behaviour patterns with less human labour. Animal behaviour is an indicator of health (Robert, White, Renter, & Larson, 2009), and monitoring cattle activity may be a useful measure to identify risk of disease (Robért et al., 2011), detecting oestrus or unhealthy motion (Hanson & Mo, 2014). In addition, accelerometers have been successfully used to distinguish lameness from healthy gait in dairy cows (Pastell et al., 2009). Therefore, research on cattle behaviour may contribute to improve welfare management. Accelerometers are claimed to be more accurate and reliable than other activity recorders, e.g. pedometers (Frost et al., 1997) and have been be used to recognise animal behaviour patterns in cattle (Dutta et al., 2015; González et al., 2015; Guo et al., 2009; Ledgerwood, Winckler, & Tucker, 2010; Martiskainen et al., 2009; Müller & Schrader, 2003;

Watanabe et al., 2008), goats (Moreau, Siebert, Buerkert, & Schlecht, 2009) and reindeer (Body, Weladji, & Holand, 2012).

For research purposes, activity sensors can be a tool to collect extended information about foraging behaviour, migration and habitat selection. Such knowledge can increase accuracy for management decisions to optimise animal performance, welfare and environmental outcomes (González et al., 2015), providing a potential to improve pasture administration, increase utilization efficiency and maximise profits. Classification of cattle behaviour on pasture is interesting for several purposes, e.g. finding variations in activity due to breed, reproduction status (pregnant or accompanied by calf), seasonal variations and nutrient uptake. Grazing behaviour is particularly important for survival of production animals (Kilgour, 2012) and lying behaviour can be a measure of cow comfort (Ledgerwood et al., 2010; White et al., 2008).

There is no current standardised classification method of animal behaviour based on data from activity sensors, and due to large areas, rugged terrain and low visibility conditions, classification data sets are particularly time consuming to collect for cattle in extensive grazing conditions observations (Augustine & Derner, 2013; Ungar et al., 2005). Different statistical methods have been trialled to classify behaviour based on data from several types of activity sensors. Machine learning methods (MLM) have become interesting for prediction of animal behaviour in ecological studies (Olden, Lawler, & Poff, 2008). MLM make a prediction of the output from the given observed inputs (Kodratoff & Michalski, 2014). For classification of cattle behaviour MLM includes decision tree learning such as classification trees (Robert et al., 2009; White et al., 2008), regression trees (Ungar et al., 2005) or the combining classification and regression tree (CART) analysis (Augustine & Derner, 2013; de Weerd et al., 2015). In R, there are developed several packages to create classification trees by using different kind of algorithms (R Development Core Team, 2016). It is shown in a comparison study that the evtree package achieved similar and mostly better accuracy in prediction, when compared to three other packages in R (Grubinger, Zeileis, & Pfeiffer, 2014).

In addition to MLM, tri-axis accelerometers on cattle have provided classification of 80-90% by discriminant functions (Watanabe et al., 2008). Data from dual-axis accelerometers has provided 84-97% classification for roe deer by discriminant function (Gottardi et al., 2010), 93% classification for red deer by tree method (Löttker et al., 2009) and 98% classification for Japanese black bear by Mann-Whiney U-tests (Yamazaki et al., 2008). For cattle, support vector machines have been tested on data from tri-axis accelerometers with an overall classification of 68% (Martiskainen et al., 2009). Body et al. (2012) developed the recursive model, to validate and monitor dual-axis activity sensors to predict continuous values of activity on reindeer, giving a classification of 85-87%. This new method was compared to the tree classification method and the standard model (based on simple logistic regression), where the recursive model gave unbiased results while the two others were dependent on the validation data set. Guo et al. (2009) used Hidden Markov models (HMM) combined with long-term track prediction based on GPS data to predict individual cattle behaviour. Ledgerwood, Winckler, & Tucker (2010) used linear regression to find that the tri-axis Onset Pendant G data logger had a >99 % accuracy to video observations of standing and lying behaviour in dairy cattle.

The number of behaviours classified varies between different studies. Binary classification is common, e.g. by finding a threshold of active versus inactive behaviour (Body et al., 2012). Some studies use the dominant behaviour of every observation in their data (Relyea, Ortega, & Demarais, 1994; Van Oort, Tyler, Storeheier, & Stokkan, 2004). Classification has been trialled to distinguish as many as 8 behaviours (Martiskainen et al., 2009) or simply to differentiate between 2 behaviours, e.g. lying and standing (Ledgerwood et al., 2010). White et al. (2008) made classification trees based on activity data from leg-attached dual-axis accelerometers classifying 76.5% of five behaviours and 98.3% of two behaviours (lying vs. standing). Augestine & Derner (2013) found that classification trees give good predictions by data from dual-axis accelerometers attached to neck collars with 87-92% classification for binary (grazing vs. non-grazing) behaviour and 84% classification for multiple behaviours (four categories), suggesting that classification rate decreases when adding more behaviours to the model.

Previous studies have found possibilities to classify and validate data from activity sensors in various statistical models. However, there are weaknesses in validation of data to classify actual behaviour. A disadvantage of most classification methods is that they require a training set for every study conducted (González et al., 2015). To reduce the need of training sets and calibrating sensors, it would be a significant improvement to find a trustable methodology to validate activity data collected from various activity sensors (Anderson, Estell, & Cibils, 2013). Thereafter, accurate data is essential to enable the use of such validation method. Due to deficient development in this field, more research is needed to make valid predictions.

The study objective for this thesis is to find a method for behaviour classification based on observations and data from dual-axis activity sensors on free-ranging cattle in a forested habitat. Classification of behaviour by activity recording is beneficial to provide an overview of activity levels correlated to the large-spanning range of cattle behaviour. However, for this study the most interesting behaviour was grazing, corresponding to foraging and nutrient uptake. Classification trees were conducted with intention to 1: classify binary behaviour (high vs. low activity), 2: classify grazing as individual behaviour in addition to high and low activity and 3: classify all high-activity behaviours (grazing, walking and other) individually, in addition to low activity. The binary classification tree provided highest classification accuracy, while dividing behaviour into more categories increased misclassification.

2. Material and methods

2.1 Study area

The study was conducted in the months of June, July and August 2015 in Stange and Romedal municipality, county of Hedmark, Norway (60°36'N, 11°24'E). The area is a common forested land of 150 square km owned by farmers in the two municipalities. During the study period, precipitation in the area (Ilseng weather station) was 217 mm and average temperature was 14.1°C with maximum temperature of 25°C and minimum temperature of 4°C (Meteorologisk institutt, 2015). The area is located 300-450 meters above sea level in southern boreal forest vegetation zone.

2.2 Cattle

17 cattle from 6 different farmers were included in the study. The study animals were mainly of the beef cattle breeds Hereford, Charolais and crossbred beef cattle. 1 of the study animals was a steer of the Norwegian red. The average age of beef cattle was 5 years old, ranging from 2 to 10 years, 12 cows were with nursing calf, the remaining were without calf.

2.3 GPS collars, programs and equipment

The cattle were equipped with Followit Tellus Medium Plus GPS collars with integrated dual-axis accelerometer (Followit Lindesberg AB, 2013). Calibration and programming of the collars were done according to the instruction manual, before attachment to any cattle. The collars were programmed by a configuration schedule through Tellus Project Manager (TPM). The GPS receivers on the collars were programmed to fix positions every 5 minutes. From the moment the transceiver starts searching for GPS signals, the activity sensor records activity every second on two axes, X and Y. The X-axis records “nodding” movement and the Y-axis records “shaking” movement. The time required to fix the position of the animal is simply called time to fix (TTF). Animal activity is recorded within TTF and therefore TTF was set to a minimum of 30 seconds to ensure sufficient activity data and a maximum of 90 seconds to have enough time to prepare for the next sequence. According to recommendations from Followit, the sensitivity is primarily set to medium sensitivity, thereafter tested and adjusted to the specific study species. After a test on cattle in paddocks on-farm, the sensitivity of the activity sensors was set to the highest sensitivity. Ethograms were tested and compared to the collected data of the collars. The 17 cattle participating in the study were equipped with their respective collar the day of release into the forest pasture area. Collars were attached to the neck of the cattle, with GPS receiver and antenna housing being on top and the main housing of activity sensor hanging down as a cowbell (Figure 1).

Figure 1: Hereford cow with Tellus Medium Plus GPS collar from Followit. Photo: Morten Tofastrud.

An internet based positioning portal, Followit Geo™, located at http://geo.followit.se/ gave position information of the GPS collars using GSM network (Followit Lindesberg AB, 2015), making it possible to observe movement during the study and to find the cattle for observation in the wide forest area. The mobile application WhatISee (Heuser, 2009) was used on iPad Air and iPad Mini (Apple, Cupertino, USA) to register the behaviour observed. The application was programmed to the desirable length of observation recording (90 seconds) and assigned the titles of the behaviours of interest. A Garmin Forerunner® 110 GPS watch or regular watches synchronized with GPS time were used by the observers to start the observation sequences at the correct time.

2.4 Behaviour observation

Cattle were individually observed during hours of daylight in *series* of preferably 10-12 observation *sequences*. Every sequence was synchronized with the position fixation every 5 minutes and lasted for 90 seconds due to the settings of maximum TTF. Observation series were preferably conducted with no interruption between sequences. When observation series was cancelled (e.g. if cow went out of sight) with less than 5 sequences observed, data was not saved or later removed from the data set. The ethogram contained 9 behaviours: Grazing, Walking, Standing, Standing ruminating, Standing unknown, Lying, Lying ruminating, Lying unknown and Other. Acronyms were created for simplicity of observation in the field (Table 1). Grazing included eating grass and feed searching behaviour while standing or slightly moving with head held down towards the ground. Walking was considered as all movement, also running, with the head up from the ground. When the animal stood on all four legs with no movement and head raised from the ground, the behaviour was considered as Standing. If the animal was ruminating or had its head out of sight while standing, behaviour was considered as Standing ruminating or Standing unknown, respectfully. Same criteria as standing behaviours given for Lying, Lying ruminating and Lying unknown, except animal is lying down on the ground. Behaviour considered as Other was used for behaviours that could not be defined within the previous, e.g. scratching, drinking, shaking the head and butting other animals or objects.

Table 1: Ethogram describing behaviours observed in the field.

Behaviour with acronym	**Description**
Grazing (G)	Standing or slight movement with head towards the ground
Walking (W)	Distinct movement in a direction
Standing (S)	Standing still with head raised from the ground
Standing ruminating (SR)	Standing still while ruminating
Standing unknown (SU)	Standing still with head out of sight
Lying (L)	Lying down on the ground
Lying ruminating (LR)	Lying down on the ground while ruminating
Lying unknown (LU)	Lying down with head out of sight
Other (O)	All behaviours that do not fit into the other categories

For every observation sequence of 90 seconds every change of behaviour was registered by the observer and saved in the application. After each observation series of one animal, data was copied to a note on the iPad and deleted from the WhatISee application before starting a new observation series on another animal.

2.5 Data processing

Data collected from the GPS collars was uploaded and sorted in Microsoft Office Excel 2010. Time difference of 2 hours due to GMT and summertime was adjusted. Both X and Y values in the data set are determined by activity within TTF, ranging from 0 to 90, due to maximum TTF. Behaviour observation data within TTF and activity data connected to the observations with correct positioning, was added to the data set. For every sequence, an individual ID was made, consisting of collar number, date and time. The *dominant behaviour* of each sequence was determined, providing one behaviour per sequence. A total of 1105 sequences, giving almost 28 hours of total behaviour observation, were considered valid for further classification. Data in Excel was transformed to a text file for easier transfer to the statistical software.

2.6 Activity variables

In addition to observed behaviour, it was necessary to have usable variables explaining sensor activity and movement. Firstly, it was needed to find valid values for X and Y. Since TTF differed from 30-90 seconds, this had to be corrugated for in the X and Y activity. To find the average activity value for every second within TTF, both X and Y were divided with TTF and the new variables were called X_t and Y_t, respectively. Secondly, a variable called *distance to previous*, adding the GPS position, included the distance between each 5-minute observation sequence. Thirdly, two variables combining X and Y was made, a *vector* was calculated as the length from 0 to the point where X_t and Y_t meet when the values are put in a graph. A tangent of the *angle* of the vector from point 0 was calculated to indicate the ratio between Y_t and X_t values in the vector. Finally, there were five different variables of activity and movement for classification: X_t, Y_t, distance to previous, vector and angle.

2.7 Density of behaviours

Data analysis was performed with R version 3.2.4 (R Development Core Team, 2016). A distribution overview of dominant observed behaviours and average activity values is shown in Table 2. In addition, a density plot was conducted by using the ggplot2 package in R, for each of the variables X_t (Figure 2), Y_t (Figure 3) and vector (Figure 4), illustrating how activity data relates to each behaviour observed.

Table 2: Distribution of dominant observed behaviours (n), average activity values and respective standard deviations (SD).

Dominant observed behaviour	N	Average X_t activity	SD	Average Y_t activity	SD
Grazing	385	0.38	0.08	0.36	0.08
Lying ruminating (LR)	203	0.12	0.09	0.17	0.11
Lying unknown (LU)	9	0.09	0.09	0.10	0.10
Lying	109	0.05	0.08	0.06	0.08
Other	60	0.29	0.13	0.29	0.12
Standing ruminating (SR)	75	0.17	0.11	0.17	0.11
Standing	149	0.17	0.13	0.17	0.12
Standing unknown (SU)	13	0.21	0.11	0.17	0.10
Walking	102	0.36	0.10	0.34	0.10
Total	1105	0.25	0.16	0.25	0.15

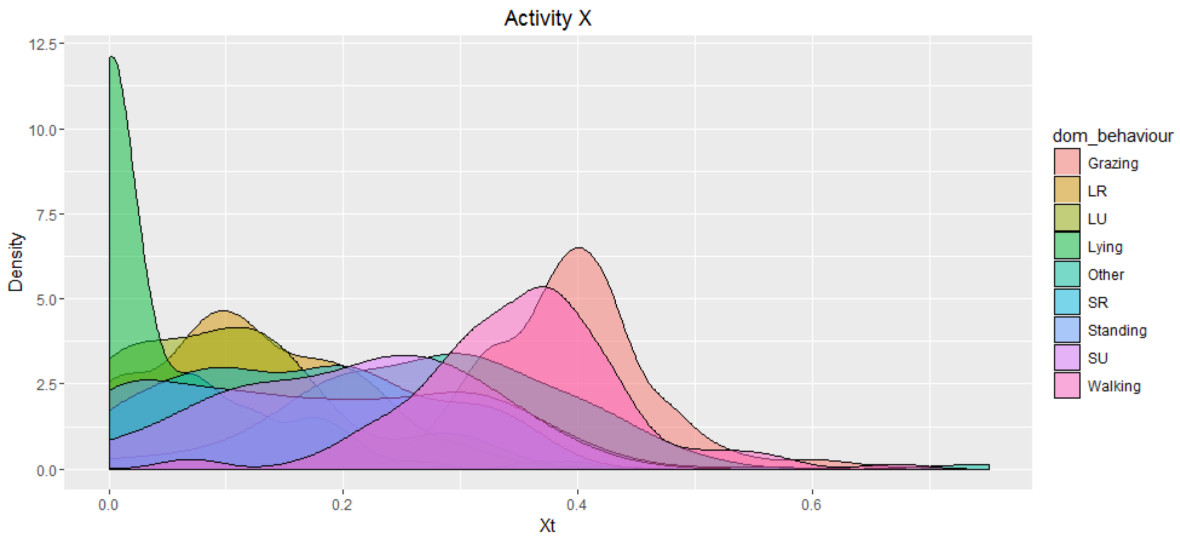

Figure 2: Density plot with correlation between dominant observed behaviour in all sequences and data from the X axis of the activity sensors, based on X_t.

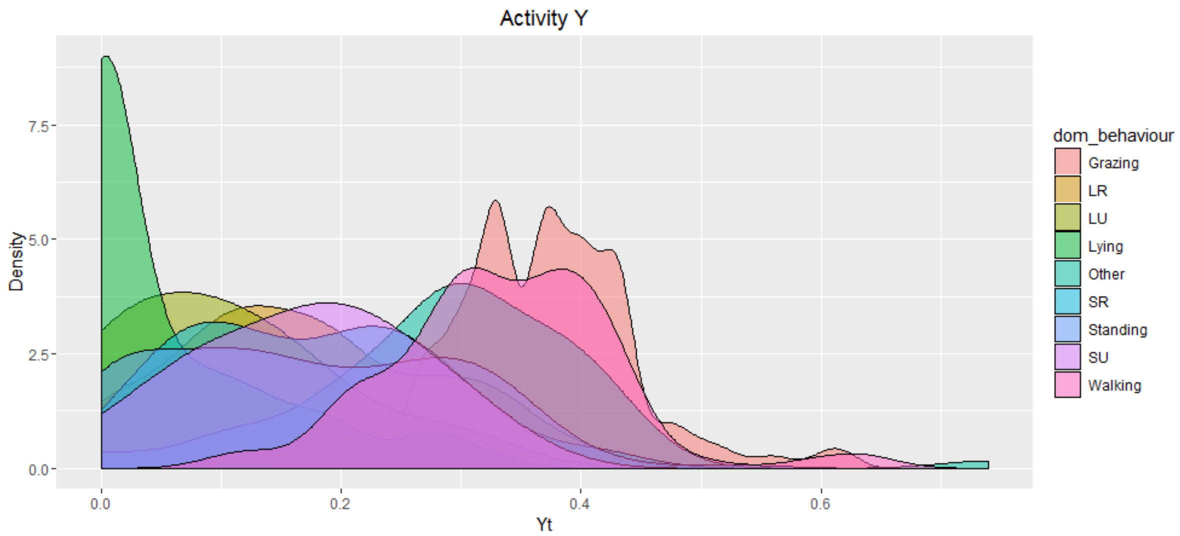

Figure 3: Density plot with correlation between dominant observed behaviour in all sequences and data from the Y axis of the activity sensors, based on Y_t.

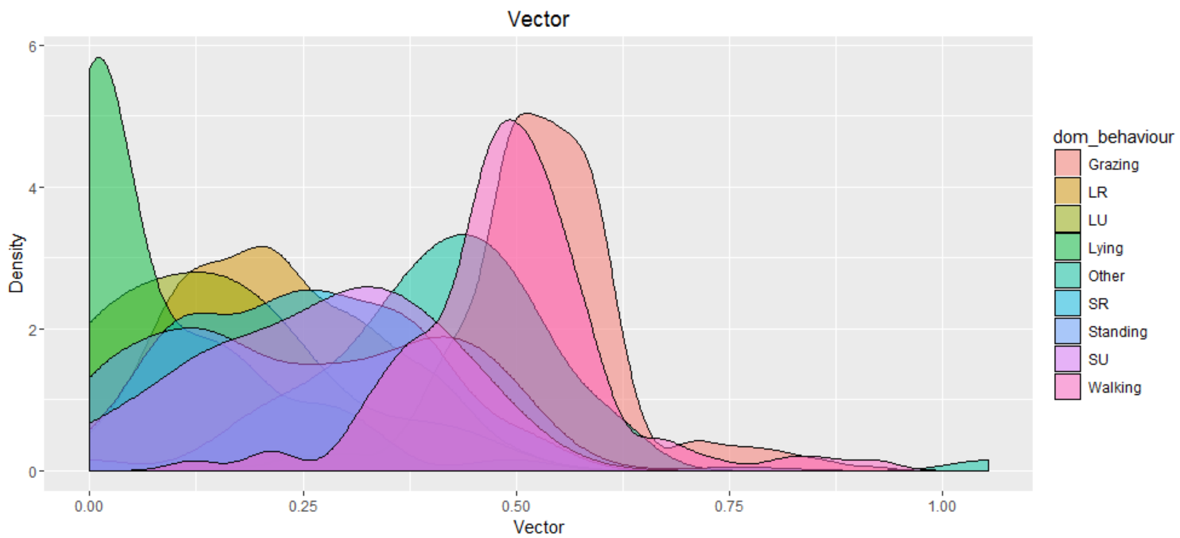

Figure 4: Density plot with correlation between dominant observed behaviour in all sequences and data from vector based on X_t and Y_t combined.

All density plots show a peak of low activity related to Lying, suggesting lying behaviour as relatively easy to classify, agreeing with White et al. (2008) who classified 96.4% of lying behaviour by classification tree. However, Grazing and Walking are relatively highly valued and seem to be closely related to the same activity levels of X_t, Y_t and vector. Observed behaviours grouped as Other showed values similar to Grazing and Walking, particularly for the variables Y_t and vector, while somewhat more evenly distributed by X_t. The density plots therefore indicate that the high-level behaviours Grazing, Walking and Other may be particularly difficult to distinguish, the same applied to the low-activity behaviours Standing, Standing ruminating, Standing unknown, Lying, Lying ruminating and Lying unknown.

2.8 Building classification trees

Density plots indicated possible difficulties in classifying all nine behaviours with classification trees. Therefore, decision was made to divide behaviours into categories, firstly a binary categorisation to classify low and high activity. Secondly, Grazing was considered the behaviour more interesting to classify, while the two other high-activity behaviours, Walking and Other, could be merged into the same category. Thirdly, despite the fact that high-activity behaviours seemed to be related, it was interesting to see if the classification tree could distinguish all three of them. The six remaining low-activity behaviours were all merged into the same category. Finally, categorisation resulted in three versions for classification:

1. High and Low. High included Grazing, Walking and Other while Low included all standing and lying behaviour.
2. Grazing, High and Low. High included Walking and Other while Low included all standing and lying behaviour.
3. Grazing, Walking, Other and Low. Low included all standing and lying behaviour.

Three packages in R were trialled: **evtree**, **party** and **rpart**, all based on machine learning methods using different algorithms for building classification trees. The evtree package performed the best classification rate and was chosen for further classification. In development of classification trees, 70% of observation sequences were selected in a training set to develop the algorithm for classification. Thereafter, the remaining 30% of observation sequences were selected for a validation dataset by testing the algorithm for the actual classification. Out of the 1105 observation sequences, 777 and 328 sequences were used for training and validation, respectfully. In addition to behaviour categories, the variables X_t, Y_t, vector, angle and distance to previous were included in the model to build classification trees in all three versions.

3. Results

All classification trees were built by X_t, vector and distance to previous position as splitting variables, chosen by the algorithms.

3.1 Classification tree with binary categories

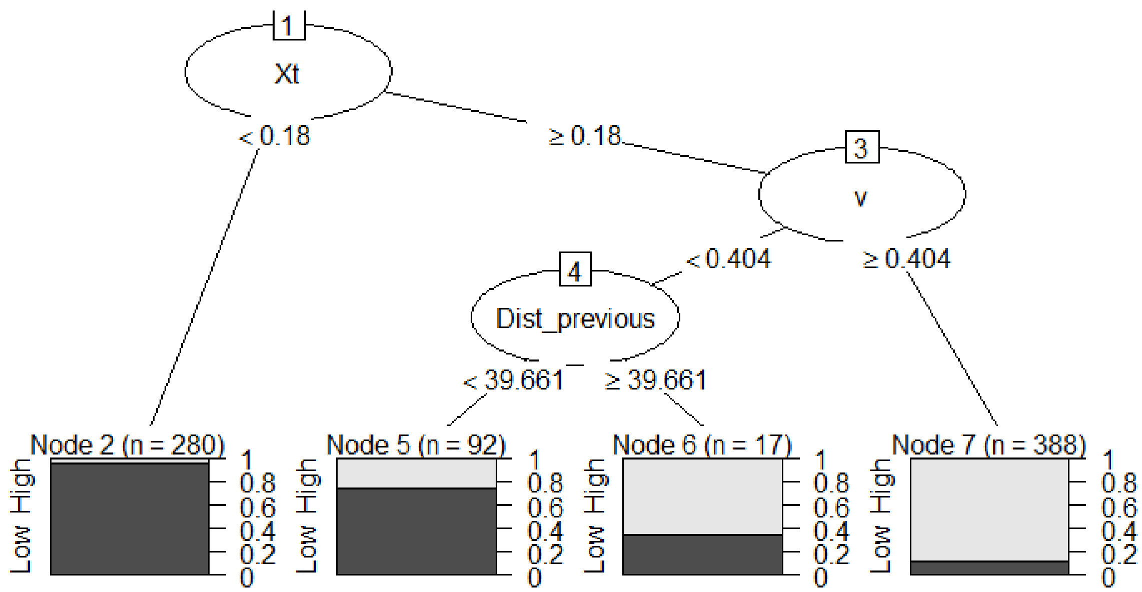

Figure 5: plot of classification tree from training set. Variables chosen by the algorithm for classification: Xt, vector and distance to previous. Total number of sequences used for classification: 777.

In version 1, behaviours were categorised as either high or low. X_t was the first splitting variable, classifying most behaviours as low when <0.18. X_t being ≥0.18, vector was chosen as the second split. Vector being ≥0.404 classified most behaviours as high while being <0.404, distance to previous was chosen as third split. Distance to previous was split by < or ≥39.661 meters, classifying behaviour as relatively low or relatively high, respectfully. Total classification was 88.4% for training set and 89.3% for validation set.

Table 3: Classification of data from training and validation set *in classification tree, version 1. Behaviour categorised as High or Low.* ***.*** *Correct classified behaviour category is shown in boldface numbers on the diagonal.*

Training set					
Predicted behaviour category [a]	Observed behaviour category		Estimate [b]	Misclassification [c]	Classification [d]
	High	Low			
High	**351**	54	405	0.133	86.7%
Low	36	**336**	372	0.097	90.3%
Total [e]	387	390	777	0.116	88.4%
Validation set					
High	**143**	18	161	0.112	88.8%
Low	17	**150**	167	0.102	89.8%
Total [e]	160	168	328	0.107	89.3%

[a] Occurred misclassifications of a behaviour category as another category can be seen within each column.

[b] Total number of behaviours predicted by the classification model for each behaviour category.

[c] Misclassification of the predicted behaviour category.

[d] Classification percentage of predicted behaviour category

[e] Total number of sequences in the data set used in the classification.

3.2 Classification tree with 3 or 4 categories

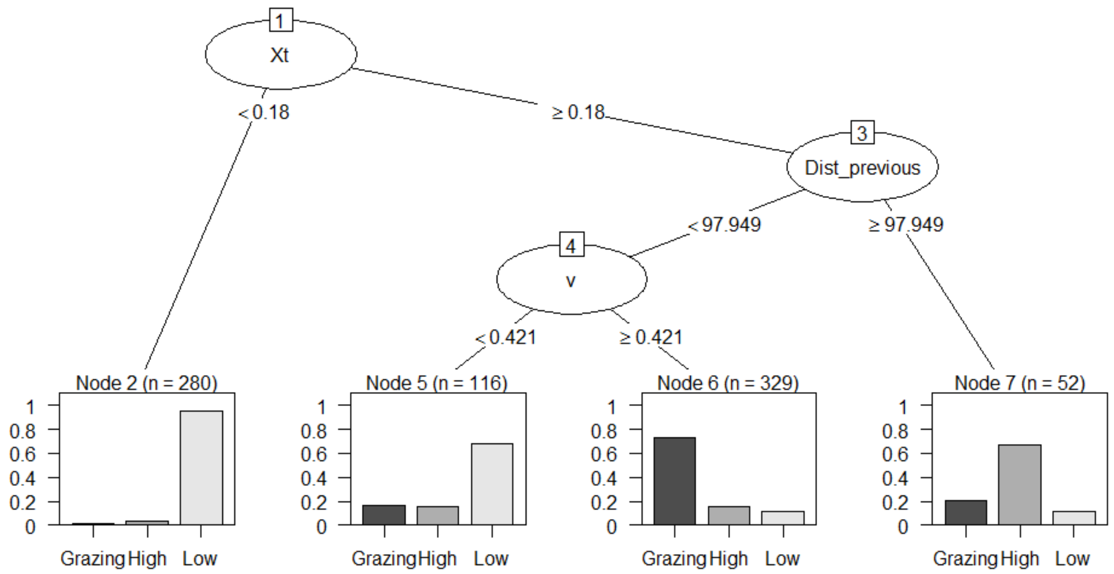

Figure 6: plot of classification tree from training set. Variables chosen by the algorithm for classification: X_t, vector and distance to previous. Total number of sequences used for classification: 777.

In version 2, behaviours were categorised as grazing, high and low. X_t was the first splitting variable, classifying behaviour as low when <0.18. X_t being ≥0.18 the distance to previous variable was chosen as second split. Distance to previous <97.949 meters chose vector as a third split and ≥97.949 meters classified most behaviours as high. Vector was split by < and ≥0.421, classifying behaviour as low or grazing, respectfully. Total classification was 80% for training set and 80.8% for validation set.

Table 4: Classification of data from training and validation set *in classification tree, version 2. Behaviour divided into three categories: Grazing, High and Low. Correct classified behaviour category is shown in boldface numbers on the diagonal.*

Training set						
Predicted behaviour category [a]	Observed behaviour category			Estimate [b]	Misclassification [c]	Classification [d]
	Grazing	High	Low			
Grazing	**239**	53	37	329	0.276	72.4%
High	11	**35**	6	52	0.337	66.3%
Low	22	27	**347**	396	0.124	87.6%
Total [e]	272	115	390	777	0.20	80%
Validation set						
Grazing	**93**	19	10	122	0.238	76.2%
High	9	**16**	2	27	0.407	59.3
Low	11	12	**156**	179	0.128	87.2%
Total [e]	113	47	168	328	0.192	80.8%

[a] Occurred misclassifications of a behaviour category as another category can be seen within each column.

[b] Total number of behaviours predicted by the classification model for each behaviour category.

[c] Misclassification of the predicted behaviour category.

[d] Classification percentage of predicted behaviour category

[e] Total number of sequences in the data set used in the classification.

For version 3, behaviours were categorised as Grazing, Walking, Other and Low. Splits in trees were identical and classification was similar to version 2. Total classification in version 3 was 79.7% for training set and 80.2% for validation set. However, in version 3, Other was not predicted by the classification tree. None of behaviours observed as Other were classified as Other. Therefore, it was decided to exclude further results of version 3.

4. Discussion

4.1 Method discussion

Errors of GPS due to tree canopy may be a disturbance for position accuracy. However, activity data used for classification were all supported by 3-dimensional locations, meaning 4 or more satellites are involved, thus providing relatively accurate positions (Rempel, Rodgers, & Abraham, 1995). Some GPS collars had more wiggle room or slightly different position on the neck due to inconsistent tightening or an additional collar. Low consistency in state of the numerous collars could be a source of error in activity recording. There are suggestions that the individual fit of collars to cattle may be an important factor for activity recording (Schauer, 2003). However, Müller & Schrader (2003) found highly significant correlation between accelerometers and actual activity both individually and when two accelerometers were attached to the same animal. An advantage of the present study was a relatively high number of animals; multiple collars can contribute to wipe out such an error source.

Selection and categorisation of behaviours for observation can be discussed. During the observation period, we found Grazing behaviour to consist of multiple actions in the field. Cattle could be searching for food or eating vegetation growing higher than the grass, suggesting that browsing and searching for food could be included as individual behaviours in addition to Grazing. However, grazing can occupy more than 95% of all foraging behaviour (González et al., 2015), meaning that grazing, browsing and searching for food might as well be merged into the same category.

Previous study sites for observation and collection of activity data varies from flat grasslands (Augustine & Derner, 2013), paddocks with little or no vegetation (González et al., 2015; Guo et al., 2009; Turner et al., 2000), dairy housings (Diosdado et al., 2015; Hanson & Mo, 2014; Ledgerwood et al., 2010; Martiskainen et al., 2009) to feedlot research stations (Robért et al., 2011). However, in present study, behaviour is observed in a hilly area dominated by forest and other vegetation, and behaviour might be different on flat grasslands or in man-made conditions. Cattle herds kept in extensive rangeland grazing situations might show variations in behaviour compared to cattle being intensively managed in small, familiar farm sites such as paddocks, possibly even more if compared to indoor behaviour (Turner et al., 2000). Behaviour may in addition to site be affected by cattle type (beef cattle, dairy cow), breed, age, sex etc. Time of grazing is similar among breeds or mixes of breeds, while travel distance and bite rate (bites per minute) can differ from different breeds or mixes (Funston, Kress, Havstad, & Doornbos, 1991), suggesting different degree of nutrient uptake according to breed. For present study, observations were only conducted during hours of daylight. Rumination and resting behaviours occur more frequently at night than during the day and increased grazing behaviour has been observed in conjunction with sunrise and sunset (Kilgour, 2012). Observations in night-time and in association with sunrise and sunset would therefore be an interesting additional factor to study the range of behaviours in a bigger picture.

There are classification differences between sensors attached to the neck and those attached to a leg, at least for lying behaviour. Martiskainen et al. (2009) found 80% correct classification for lying when sensor was attached to the neck, while Trénel, Jensen, Decker, & Skjøth (2009) showed 100% correct classification for lying when attached to leg. A question of comparability to similar studies arises due to differences in type of sensor used; dual- or tri-axis accelerometers, position of the sensor, management conditions and statistical classification methods for behaviour. However, methods of present study are comparable to the work of Augestine & Derner (2013), whose study included similar factors: using classification trees to classify binary behaviour and grazing behaviour based on data from dual-axis activity sensors attached by neck collar, with similar classification results.

4.2 Result discussion

Classification trees were built with three out of five pre-selected activity variables; the variables X_t, vector and distance to previous. The last two variables, Y_t and angle, were not chosen by the algorithms in R, indicating that these variables are considered less important for classification. X_t and Y_t show strong correlation due to similar average activity levels (Table 2). The reason why X_t is chosen over Y_t as a splitting variable might be that total X_t activity has slightly higher SD, in addition to higher activity values in Grazing and Walking compared to Y_t. Nevertheless, since vector is based on activity from both X- and Y-axis, Y_t could indirectly be considered as a contributing variable for classification. The correlation between X_t and Y_t might provide insufficient variation in the angle variable, possibly explaining why angle was not a splitting variable. Distance to previous seems to be an important factor to classify high activity behaviours, including Grazing (Figure 5 and 6). However, distance is varying between 40 meters, chosen as third split for version 1, and 98 meters, chosen as second split for version 2. This proposes distance to be more important when adding Grazing as an individual category in version 2, not surprising since High consists mostly of the obvious behaviour movement: Walking. Augestine & Derner (2013) also found distance travelled in a 5-minute interval to be an important factor to predict grazing behaviour, supporting the findings of present study.

Total classification was 89.3% and 80.8% for version 1 and 2, respectfully. The number of behaviour categories seems to interfere with the prediction accuracy of the classification tree; adding one more category decreased the overall classification rate, supported by results of previous studies (White et al., 2008). Binary classification trees show better accuracy in prediction than a classification tree with four different categories (Augustine & Derner, 2013). Nevertheless, having three or four categories in the classification tree did provide similar classification (80.2% in version 3), disregarded the fact of difficulty of predicting Other behaviour. In version 3, none of the behaviour categories were classified as Other. Half of behaviour observed as Other was classified as either Grazing or Walking, the remaining half was classified as Low. The reason might be relatively few observations of this category; only 60 out of 1105 sequences had Other as dominant behaviour (Table 2), compared to Grazing and Walking which was the dominant behaviour observed in 385 and 102 sequences, respectfully. In addition, the behaviour Other is all behaviours that could not fit within the 8 main behaviours, leading to distribution over all levels of activity. Even though both X_t and Y_t values are relatively high, the standard deviation of both is among the highest for Other behaviour, possibly explaining the classification difficulty.

4.3 Conclusion

Classification of binary behaviour (high vs. low) gave relatively high classification rate: 89.3%, whereas adding Grazing as an individual category to High and Low, gave somewhat lower classification rate: 80.8%. Having Grazing, Walking and Other as individual categories did not decrease classification rate more than 0.6%. According to the results, behaviour classification is less accurate when adding more than two activity categories in classification trees. Adding three or four categories assumed similar classification as in binary classification. However, Other was classified as either high or low activity, making this assumption hard to determine. Classification difficulties are likely due to inconsistency in activity data when several behaviours are correlated to the same levels of activity.

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