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M. Decandia[a], V. Giovanetti[a*], G. Molle[a], M. Acciaro[a], M. Mameli[c], A. Cabiddu[a], R. Cossu[b], M.G. Serra[a], C. Manca[a], S.P.G. Rassu[b], C. Dimauro[b].

[a]AGRIS Sardegna, 07040 Olmedo, Italy.

[b]Dipartimento di Agraria, Università di Sassari, viale Italia 39, 07100 Sassari, Italy.

[c]Electronic Systems, via Sassari 101, 07041 Alghero, Italy.

*Corresponding author.

E-mail addresses: mdecandia@agrisricerca.it (M. Decandia), vgiovanetti@agrisricerca.it (V. Giovanetti), gmolle@agrisricerca.it (G. Molle), macciaro@agrisricerca.it (M. Acciaro), ma.mameli@libero.it (M. Mameli), acabiddu@agrisricerca.it (A. Cabiddu), rossellacossu@uniss.it (R. Cossu), gserra@agrisricerca.it (M.G. Serra), cmanca@agrisricerca.it (C. Manca), pgrassu@unss.it (S.P.G. Rassu), dimauro@uniss.it (C. Dimauro)

Abstract

Monitoring behaviour of grazing animals is important for the management of grazing systems. A study was run to discriminate between the main behaviours (grazing, ruminating and other activities) of sheep at pasture wearing a halter equipped with an accelerometer (BEHARUM device), and to identify the epoch setting (5, 10, 30, 60, 120, 180 and 300 s) with the best performance. The BEHARUM device includes a three-axial accelerometer sensor and a force sensor positioned under the lower jaw of the animal. The halter was fitted to eight Sarda dairy sheep that rotationally grazed either a spatial association (mixture) or a time association of berseem clover (*Trifolium alexandrinum* L.) and Italian ryegrass (*Lolium multiflorum* Lam.) for 6 hours day^{-1}. The behaviour of the animals was also video-recorded. The raw acceleration and force data were processed for each epoch setting to create 15 variables: the mean, variance and inverse coefficient of variation (ICV; mean/standard deviation) per minute for the X-, Y-, Z-axis and force, and the resultant. Multivariate statistical techniques were used to discriminate between the three behavioural activities:

canonical discriminant analysis (CDA), and discriminant analysis (DA). To validate the derived discriminant functions, a bootstrap procedure was run. To evaluate the performance of DA in discriminating between the three activities, the sensitivity, specificity, precision, accuracy and Coehn's k coefficient were calculated, based on the error distribution in assignment. Results show that a discriminant analysis can accurately classify important behaviours such as grazing, ruminating and other activities in sheep at pasture. The prediction model has demonstrated a better performance in classifying grazing behaviour than ruminating and other activities for all epochs. The 30 s epoch length yielded the most accurate classification in terms of accuracy and Coehn's k coefficient. Nevertheless, 60 and 120 s may increase the potential recording time without causing serious lack of accuracy.

Keywords. Feeding behaviour; accelerometer; wireless communication technology; discriminant analysis.

1. Introduction

Monitoring the behaviour of grazing ruminants is important to understand how animals meet their requirements in pastoral systems and to achieve optimal plant production, animal forage intake and performances (Carvalho, 2013). Since observing animal behaviour is a labour-intensive and difficult task, whether it is performed with direct observations or through video recordings, most research has concentrated on recognizing feeding behaviour of ruminants from animal attached sensors. A type of sensor that has recently become widespread in research studies is the tri-axial accelerometer, since it is small, inexpensive, and easy to wear (Brown *et al*., 2013).

Accelerometers have been widely used to automatically detect and classify several behaviours in cattle, e.g. *oestrus* detection (Ueda *et al*., 2011), walking (Robert *et al*., 2009) feeding and standing activities in a free-stall barn (Arcidiacono *et al*., 2017), sleeping posture (Fukasawa et al., 2018) and time (Hokkanen et al., 2011), and eating, ruminating and resting activities (Watanabe *et al*., 2008).

Fewer research studies have been conducted to classify sheep behaviours than cattle behaviours. Umstätter *et al*., (2008) used integrated pitch and roll tilt sensors, and found that they could distinguish between two categories: active and inactive, with more than 90% accuracy. Other studies on sheep behaviour used the collar attached Actiwatch accelerometer system for classifying activity levels and detecting diurnal rhythms

(Piccione *et al.*, 2010, 2011). Other authors (Nadimi *et al.*, 2012; Nadimi and Søgaard, 2009) used the ADXL202 accelerometer to detect grazing, lying down, standing, walking, mating and drinking in sheep with a mean accuracy of 76.2%. Alvarenga *et al.*, (2016) successfully identified grazing and non-grazing states, with accuracies higher than 83%, in grazing sheep wearing an accelerometer under the lower jaw. More recently Giovanetti *et al.*, (2017a), positioning a device containing an ADXL335 accelerometer sensor in the same place, were able to classify grazing, ruminating and resting behaviour of sheep at pasture with an overall accuracy of 93%.

Tri-axial accelerometer based devices can acquire and store information internally, thus consuming very little battery power. However, the amount of data that can collected is limited by the size of the memory card within the device. On the other hand, data can be directly transmitted to a central receiver for subsequent processing. This practice, however, requires a high power consumption (Vázquez Diosdado *et al.*, 2015).

The sampling frequency of such devices usually ranges from 8 to 100 Hz, thus producing an enormous quantity of data, proportional to the sampling frequency, which can lead to a rapid depletion of the memory device and to high costs in terms of battery consumption caused by sending and receiving large data sets. These restrictions could be overcome by undertaking some form of preliminary processing of the accelerometer data on the device itself settling and applying to the data stream, for a given sampling frequency, an optimal aggregation window (called epoch).

Optimizing the epoch setting, without compromising classification accuracy, could imply a number of advantages. Short epoch settings could increase the labour involved in processing data, deplete the memory device, decrease the battery duration and may also cause erroneous attribution activities during processing. Actually, if an epoch shorter than the period of time an activity occurs is used, the number of false positive classifications for dynamic activities could increase probably due to transitioning between different activities or body shifts during static activities (Robert *et al.*, 2009). Conversely, optimized longer epoch settings might reduce the memory depletion and increase the battery duration without compromising the performance of the sensor. Nielsen, (2013) distinguished grazing from non-grazing behaviour with a 3D activity sensor that correctly classified the behaviours of dairy cows with a relatively high accuracy when the epoch was set at 5 s, 5 or 10 minutes. Other authors, as Vázquez Diosdado *et al.*, (2015), while classifying lying, standing and feeding behaviours in dairy cows, reported a small increase in the decision-tree classification algorithm performance at the largest window size of 10 minutes if compared with 1 and 5 minutes epoch settings. In the present research, a customized tri-axial accelerometer based sensor, able to either store data in a micro SD card or send them to a remote computer, was used. In the future perspective of data pre-processing in the device itself, determining the optimum device settings before field application is crucial, because they could impact on monitoring system accuracy as well as on the effective battery and memory life.

The objectives of this study were: 1) to develop an algorithm based on the multivariate statistical analysis to discriminate the main behaviours (grazing, ruminating and other activities) of sheep at pasture equipped with a customized tri-axial accelerometer based sensor named BEHARUM; 2) to determine the performance of the algorithm in terms of accuracy, sensitivity, specificity, precision and Coehn's k coefficient, at different epoch settings (5, 10, 30, 60, 120, 180 and 300 s); and 3) to select the epoch that optimizes the system accuracy of the device.

2. Materials and methods

2.1 Experimental site and animal management

The study was conducted at Bonassai experimental farm of the agricultural research agency of Sardinia (AGRIS Sardegna), located in the NW of Sardinia, Italy (40° 40' 16.215" N, 8° 22' 0.392" E, 32 m a.s.l).

The animal protocol below described was in compliance with the EU regulation on animal welfare and all measurements were taken by personnel previously trained and authorized by the institutional authorities managing ethical issues both at Agris Sardegna and the University of Sassari.

The study is part of an experiment conducted in spring 2016, from 1 March to 9 May, with 48 mature lactating Sarda dairy sheep that rotationally grazed berseem clover (*Trifolium alexandrinum* L.) and Italian ryegrass (*Lolium multiflorum* Lam.) for 6 hours day^{-1}. Two grazing treatments were used: a mixture of berseem clover and Italian ryegrass, and two monocultures (berseem clover and ryegrass) grazed in succession. In the latter case, the sheep grazed the first 3 hours on the clover and the last 3 hours on the ryegrass. The ewes were machine milked twice daily at 0700 hours and 1500 hours. During milkings, they were individually fed in the milking parlour with commercial concentrate (500 g ewe^{-1} day) split into two meals. In the remaining daytime, the animals were kept indoors and group-fed 500 g ewe^{-1} of ryegrass hay and 300 g ewe^{-1} of alfalfa hay in separate troughs. On four occasions (test days) during the experiment, eight ewes (four per treatment), with an age of 3.1±1.6 years (mean ± standard deviation), live weight of 41.3±2.8 kg, lactation stage of 73±6 days in milk and milk yield of 2062±362 g ewe^{-1} day^{-1}, were used. On each test day, after the morning milking, the ewes were carried on a trailer to the experimental plots and equipped with the BEHARUM device before the six hours of access to pasture. At the end of the grazing session, the BEHARUM devices were removed from the animals.

2.2 Description of the BEHARUM device and feeding behaviour recording

The BEHARUM device includes a halter equipped with a three-axial accelerometer sensor and a force sensor positioned under the lower jaw of the animal. Animal head and jaw movements are detected through accelerations measured in the X (longitudinal), Y (horizontal) and Z (vertical) axes (Figure 1) and force exerted by the opening jaw.

The sensors, inserted in a micro-electromechanical compact system (MEMS) with on-board peripherals, sample raw accelerations and force at a frequency of 62.5 Hz, and convert them, through an analogue-to-digital converter with a resolution of 8 bits, in digital levels ranging from 0 to 255. Then the microcontroller selects three converted values per second per axis (Giovanetti *et al*., 2017a) and force sensor. The converted data could be sent (LoRa wireless system) to a nearby computer receiver equipped with an antenna or to a remote computer through a local server using the GSM services, as well as recorded in a micro secure digital (SD) card inserted in the MEMS.

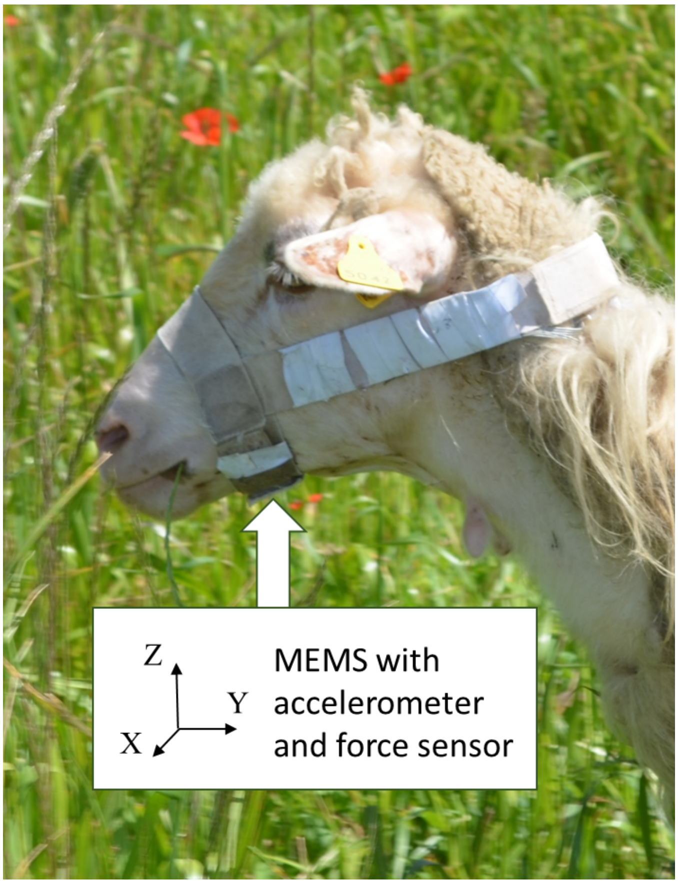

Figure 1. BEHARUM halter with accelerometer and force sensor inserted in a micro-electromechanical compact system (MEMS) positioned under the jaw.

A software package (DAS Client, Electronic System), installed on the computer, activates or deactivates the BEHARUM device and manages data acquisition. In this experiment, we adopted the recording of acceleration and force data on micro SD card.

On each test day through the 6 hours of access to pasture, the feeding behaviour of sheep equipped with the BEHARUM were video recorded, one at time, during accelerometer deployment by fixed camera (Sanyo Xacti VPC-TH1, Sanyo Electric Co., Ltd. OSAKA, Japan). Video recordings of each animal lasted 20-25 minutes. The internal clock of the camera was synchronised with the internal clock of the computer. This ensured both the camera and accelerometer were synchronized in time to allow accurate annotation of the accelerometer data after behavioural recordings were made.

2.3 Preliminary data processing

On the basis of the recorded videos, a file including the three acceleration values for each axis, the force values and one of the three behavioural activities (grazing, ruminating, and other activities) per second was created, for a total of 69975 seconds dataset. Behaviour activities were classified according to Gibb (1998). Grazing activity included the act of searching for food while walking with the head down without evidence of biting, or standing still with the head down while biting and chewing either with the head down or the head up. Ruminating activity included regurgitation, chewing and swallowing of bolus, in lying or standing position. Other activities included all the activities not taken into account in grazing and ruminating, e.g. lying down or standing without rumination, and travelling etc.. Mean (MX, MY, MZ, MF), variance (VX, VY, VZ, VF), inverse coefficient of variation (i.e. mean/standard deviation, ICVX, ICVY, ICVZ, ICVF), of acceleration data for each axis and force data, as well as the resultant mean (MRES), variance (VRES) and ICV (ICVRES) values of the three axis and force (Watanabe *et al.*, 2008), were calculated for the following epoch settings: 5 s, 10 s, 30 s, 60 s, 120 s, 180 s, 300 s.

Video recordings were coded manually assigning to each epoch the prevailing behaviour; that is to say grazing, ruminating or other activities. We considered as prevailing the behaviour with the highest percentage among the three activities performed by the animal within epoch setting. Overall, the percentage of the prevailing behaviour ranged from 50 to 100%. For that reason, we established three classes of prevalence: 50-75%, 76-99% and 100%. Afterwards we counted, for each epoch setting, how many times the prevailing behaviours were included in one of the three classes and we expressed the values obtained as a percentage of the total. For each epoch setting, data were arranged in a multivariate manner with seventeen columns including the epoch, the prevailing activity and the fifteen acceleration and force variables (MX, MY, MZ, MF, VX, VY, VZ, VF, ICVX, ICVY, ICVZ, ICVF, MRES, VRES, ICVRES). Eventually, we obtained seven datasets, one for each epoch setting under study.

2.4 Data processing

An exploratory analysis of each dataset was conducted using a one-way ANOVA model to test the effect of behavioural activities (grazing, ruminating and other activities) on all fifteen accelerometer and force variables.

The seven datasets were then submitted to two multivariate statistical techniques to discriminate between the three behavioural activities: canonical discriminant analysis (CDA), and discriminant analysis (DA). All statistical analyses were performed by using the SAS software (SAS Inst. Inc., Cary, NC). CDA was used to test the ability of the variables involved (the fifteen accelerations and force variables) in discriminating between groups (grazing, ruminating and other activities) (Mardia *et al*., 2000). In general, if d indicates the number of groups, the CDA derives d−1 linear equations, called canonical functions (CAN) that are used to predict the group to which an object belongs. The structure of a CAN is:

$$\text{CAN} = c_1X_1 + c_2X_2 + \dots\dots + c_nX_n$$

where c_i are the canonical coefficient (CC) and X_i are the values of the n involved variables. CCs indicate the partial contribution of each original variable in composing the CAN. In consequence, the higher the absolute value of a CC, the higher the weight of the corresponding variable in composing the CAN. In the present research, d was equal to 3 (the three behaviours) and, in consequence, two CANs were obtained.

The distance between groups was evaluated by using the Mahalanobis' distance, whereas the effective groups' separation was tested by using the corresponding Hotelling's T-square test (De Maesschalck *et al*., 2000). DA was then used to classify epochs into one of the three behaviours (Mardia *et al*., 2000).

To validate the derived discriminant functions, each dataset was randomly divided into training and validation dataset in the proportion of 4:1. This partition of the dataset was iterated 5000 times by using a bootstrap procedure (Efron, 1979). At each run, DA was applied to the training dataset to predict behaviours in the validation dataset and errors in assignment were recorded. To evaluate the performance of DA in discriminating between the three activities, the sensitivity, specificity, precision and accuracy were calculated, based on the error distribution in assignment, using the following equations:

Sensitivity = TP/(TP+FN);

Specificity = TN/(TN+FP);

Precision = TP/(TP+FP);

Accuracy = (TP+TN)/(TP+TN+ FP+ FN)

Where TP, TN, FP and FN are true positive, true negative, false positive and false negative counts respectively. The Coehn's k coefficient was calculated (Fleiss, 1981) to evaluate the agreement between observed and model predicted corrected for agreement that would be expected by chance, both for each behaviour and overall. The k values were judged according to the criteria of Landis and Koch (1977).

3. Results

Overall, the distribution of the three behaviours in the datasets is on average 50% grazing, 30% ruminating and 20% other activities.

The results of the ANOVA showed that the behaviour activities affected significantly all variables in each epoch apart from ICVX in the 300 s dataset (Table 1). Some variables (MY, VY, MRES and VRES) were always significantly different between the behaviours in all epochs. The same results can be observed for MX, MF and VF with the exception of 300 s, where only grazing was different from the other two behaviours. Differences between the three activities were also found in other variables but only in some epoch (Table 1). In all the other cases, only one behaviour was different from the other two.

3.1 Discrimination between behaviour activities

Regarding the allocation of prevailing behavioural activity (expressed as percentage of the total), the overall trend was an increment in the low and medium classes of prevalence (50-75% and 76-99%) coupled obviously with a reduction in the highest class (100%), passing from 5 s to 300 s epoch set (Table 2). Actually, the percentage of the prevailing behaviour included in the 100% class decreased from 98.8%, in 5 s, to 60.2% in 300 s.

In developing multivariate techniques, the MRES variable was discarded from the analysis because it made the (co)variance matrix singular due to linear dependencies with other variables. The CDA significantly discriminated between the three behaviours (Hotelling's test $P < 0.0001$) by extracting two canonical functions for each epoch set. The variation λ_1 accounted for CAN1, ranged among epochs between 0.78 and 0.93 whether the variation λ_2 explained by CAN2 ranged between 0.08 and 0.22 (Table 3).

The lowest value of error in assignment, after the bootstrap resampling, was obtained in the 30 s epoch whereas the highest value was at the 300 s epoch (Figure 2).

VRES and MZ showed the highest canonical coefficient values in CAN1 in nearly all the epochs with the exception of 5 s and 180 s, which recorded biggest values in VRES and MY and MZ and VZ respectively

(Table 3). The highest canonical coefficient in CAN2 was found in VRES in all the epochs. In all time epoch settings canonical functions separated the three behavioural activities (P < 0.001, Figure 3). In particular, CAN1 discriminates the grazing activity from the other activities. Ruminating is an intermediate process, and this is confirmed by the Mahalanobis' distances (Table 4). In fact, the highest values were observed between grazing and other activities with the only exception of 300 s where it is slightly higher than the distance between grazing and ruminating.

3.2 Performance of the discriminant analysis model

The performances of the DA model, displayed in Table 5, show that the sensitivity of the model to predict grazing was the highest in the 60 s epoch set and the specificity in the 120 s epoch set. When the model was used to predict the rumination, the specificity reached the maximum value in the 30 s setting whereas the sensitivity in the 120 s epoch setting. The 30 s epoch length was the best to predict other activities, both in terms of sensitivity and specificity. The highest precision of the models to predict grazing was recorded in the 120 s set while the highest accuracy was obtained in 30- and 60 s, the k value being 0.9 in 30-, 60-, 120- and 180 s. Ruminating and other activities behaviours were predicted with the highest precision and accuracy in the 30 s epoch with a k value of 0.8 and 0.7, respectively.

The overall accuracy values of the prediction models were similar in the range between 10 s and 120 s epochs, peaking in the 30 s epoch. The Coehn's k coefficient reached a plateau value (0.8) in the 10-, 30-, 60- and 120 s epochs.

4. Discussions

4.1 Discrimination between behaviour activities

In this study a multivariate statistical algorithm was developed, by using tri-axial acceleration data obtained from an under lower jaw mounted sensor, to classify grazing, ruminating and other activities of dairy sheep. The CDA successfully distinguished the different behaviours, although the CAN1 vs CAN2 scatter plots (Figure 3) showed different levels of separation according to the time epoch length. This fact could be due to the variation (λ_1) explained by CAN1 that reached higher values in 30-, 60-, and 120 s than in the other time epochs (Table 3), whereas CAN2 was not able to separate behaviours (Figure 3).

The Mahalanobis' distance was greater between grazing and other activities than that between grazing and ruminating in all epochs with the exception of the 300 s epoch. This is probably related to the low prevalence in this dataset, with only 60.2% of records classified in the highest class (100%, Table 2). As a consequence, the contribution of the "non prevailing activities" (i.e. the complement to the prevailing activity) within records, was higher in this case than in the other epoch sets. This indicates that increasing the aggregation time window for calculation of the means, variances and ICV from 120 s to 300 s probably flattened data distributions and limited the ability to discriminate between different behaviours such as other activities and rumination. In fact, the results of the ANOVA on the effect of behavioural activities (Table 1) show that increasing the aggregation time window (the epoch length) increases the number of variables that show at least two behavioural classes to be not significantly different. In 5 s epoch set, for example, among the fourteen variables under scrutiny, only three variables (ICVRES, ICVZ and ICVY) had, at least, two values undifferentiated between behaviours, while in 10 and 30 s epochs the variables with this response were four (ICV, ICVY, ICVZ and ICVF) and so on for the other epochs. These results highlight the limits of the ANOVA, which analyzes each variable individually, in separating the three behaviours. In consequence, the adoption of a multivariate approach, that conversely uses a set of variables to separate and assign new observations to groups, is fully justified.

VRES and MZ, showing the highest standardized canonical coefficients for CAN1 (Table 3), are the most important features for behavioural classification in all epoch settings. Therefore, grazing activity, that includes various dynamic movements such as biting, chewing and head shaking while lowering the head, can be differentiated from other behaviours by VRES that measures the total amount of variance of the acceleration signal through three dimensions, and by MZ that, in turn, represents the mean of head/jaw vertical accelerations.

In CAN2, which explained a very low part of the total variation ($0.08 < \lambda_2 < 0.22$), VRES showed the highest standardized canonical coefficient at all epochs, in agreement with what reported by Giovanetti *et al.*, (2017a) who used BEHARUM device to monitor the feeding behaviour of dairy sheep, using a 60 s time epoch. The importance of these variables in discriminating sheep behaviours was also reported by Barwick *et al*., (2018).

Conversely, Watanabe *et al*., (2008), who studied behaviour in grazing cattle, found the highest discriminant scores using the means and ICV as explanatory variables. González *et al*., (2015), with a tri-axial accelerometer attached on a collar around the neck of steers, were able to separate cattle foraging behaviour from other activities, at 10 s epoch, using the X-axis mean which corresponds to our MZ variable. Umstätter *et al*., (2008) found similar results (epoch settings 30 s), with pitch features (head up and down), our Z-axis, as the most important factor for behavioural classification for sheep wearing a collar equipped with a sensor. Alvarenga *et al*., (2016), conversely, reported that the most important feature was the means of the X-axis (forward/backward acceleration) to capture head position and level of activity related to grazing for different epoch settings (3-, 5- and 10 s). The reason of this inconsistency is unclear but may possibly be related to the different methods of accelerometer deployment, or to the different number of behavioural activities considered as well as to the different classification criteria. Moreover, some sources of signal variation may arise from differences in physical structure of animals affecting sensor orientation.

To the best of our knowledge, we did not find any result on the use of force sensor in animal behaviour studies. This sensor, that measures the force exerted by the opening jaw movements during feeding related activities, showed the highest MF and VF values when the animals performed dynamic movements (i.e. grazing and ruminating). Although the canonical coefficients of force variables were low, their contribution to the discrimination of the three behaviours has been revealed important.

4.2 Performance of the discriminant analysis model

The performance of the model changed according to the predicted behaviour (Table 5). In fact, the grazing activity showed best performance, in terms of sensitivity and precision, than the other two activities for almost all the epoch set, thus confirming the results of other studies (Giovanetti *et al*., 2017a; Nadimi *et al*., 2012). This is probably due to the higher correct true positive classification of grazing than ruminating and other activities, indicating that the classifier had problems predicting positive cases correctly in the last two classes that became most easily confused with other behaviours.

Specificity in other activities (i.e. the true negative rate) resulted higher than in ruminating and grazing for all epochs. Accuracy also was higher in other activities for almost all epochs, except for 180 and 300 s where it reached the highest value in grazing activity. The unequal number of observations for the different activities could partially explain the above modelling performance. In fact, other activities did not exceed 20% in the whole our dataset. Therefore, sensitivity and precision are probably more informative than accuracy and specificity in order to summarize performance results.

Grazing behaviour was predicted in 5 s epoch dataset with higher sensitivity (88.1% vs 84.3%) but lower specificity (86.9% vs 97.3%) and precision (86.9% vs 92.9%) than in the work by Alvarenga *et al*., (2016) on Merino ewes. The precision in the current study resulted anyway higher than that found by Marais *et al*., (2014) using a 5.12 s epoch, which was c.a. 66%. The 10 s epoch length, conversely, showed higher sensitivity (94.7% vs 91.7%) and precision (91.9% vs 89.8%) but lower specificity (90.8% vs 96.2%) in comparison with data by Alvarenga *et al*., (2016). Barwick *et al*., (2018) with the same epoch setting of 10 s found different performances in discriminating sheep grazing behaviour according to deployment position (ear, collar, leg). They actually reported the best performance in ear deployment that produced better results than our study, apart from sensitivity (92.0 vs 94.7%). Rodriguez *et al*. (2017), in an experiment with sheep, dividing their dataset in epochs of 14 s, reported performance similar to our 10 s epoch for grazing behaviour recognition. They actually found a sensitivity of 91.3%, a precision of 90.9%, a specificity of 91.9% and an accuracy of 91.6%. Moreau *et al*., (2009), even if in a study conducted with grazing goats wearing the Hobo® G Pendant Data Logger, reported a true recognition rate of eating behaviour (grazing or browsing) similar to our results for 5 (89% vs 87% respectively) and 10 s (91% vs 92% respectively).

We encountered some difficulties in comparing the performance of the BEHARUM device for epochs larger than 20 s with the literature, since few papers regarding the use of accelerometer sensor in small ruminants have been published. Moreover, a comparison of results obtained in sheep with those obtained with large animals could not be appropriate. This assumption is supported by the results observed in a study conducted with the BEHARUM device placed under the jaw of cattle at pasture. Giovanetti *et al*., (2017b), using the same device (BEHARUM), time epoch setting and statistical data analysis as in the present experiment, found that overall accuracy of 5, 10 and 30 s epochs in sheep showed higher values than those reported in cattle (79.4%, 86.4% and 89.7%, *vs* 77.5%, 82.2% and 88.8% in sheep and cattle, respectively). This was probably due to the better capability of the model, for those epochs, to predict grazing activity in sheep than cattle.

In the present experiment, the performance of the model was explored in relation to the choice of the best epoch setting. If we consider the overall model performance in discriminating the three behaviours, the best overall accuracy and k coefficient was found at 30 s epoch setting (Figure 1, Table 5) and the worst performances at the smallest (5 s) and biggest epoch setting (300 s). In sheep, contrarily to what happens in cattle (Giovanetti *et al*., 2017b; Vázquez Diosdado *et al*., 2015), when epoch setting is above 30 s, increasing the time epoch length, decreases the correct classification of behaviour. Our findings of the ANOVA analysis (Table 1) indicate that this could be probably related to the lack of significant differences of behaviours for many variables within the longer time frames, as in the case of 120 s, 180 s and 300 s epoch settings.

Looking towards the 60 s epoch we can observe a slightly lower overall accuracy (88.9% vs 93.0%) and Coehn's k coefficient (0.8 vs 0.9) than those found by Giovanetti *et al*., (2017a) and this may be due to the bigger and more varied dataset utilized in this paper than in the previous study. As a matter of fact, in the present research sheep grazed mixed grass and legume pastures whereas, in the work by Giovanetti *et al*., (2017a), animals were fed on pasture monocultures only.

Despite this slight decrease of the model performance in this study, the 60 s and 120 s epochs cannot be discarded *a priori*, because they actually show a good k coefficient (0.8 for both) as well as accuracy, which values are 88.9% and 87.6% respectively. In this current study, the overall k value indicates substantially greater classification agreement than that would be expected to occur by chance, thus indicating that the classification success of our model could be considered reasonable for most of the epochs.

Therefore, if the user's aim is to get from BEHARUM device applied to sheep the best performance of classification during short grazing periods (say one day or less), the 30 s epoch should be chosen. Alternatively, if the user's goal is mostly practical, i.e. to record good quality data for a longer periods (days or weeks) then 60 and 120 s epochs should be chosen, with the aim to save battery energy, allowing for a longer recording time.

5. Conclusions

Our results showed that the discriminant analysis of data from an under lower jaw tri-axial accelerometer can accurately classify important behaviours such as grazing and ruminating in sheep at pasture. The prediction model performed better in classifying grazing behaviour than ruminating and other activities for all epochs. The 30 s epoch length yields the most accurate classification in terms of accuracy (89.7%) and Coehn's k coefficient (0.8). Nevertheless, 60 and 120 s, may increase the potential recording time without causing serious lack of accuracy, and could be adopted for most practical purposes for monitoring sheep behaviour in extensive conditions.

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Table 1. The effect of the behavioural activities recorded in grazing sheep on the mean (M), variance (V) and inverse coefficient of variation (ICV) of acceleration values per minute along the X, Y, Z-axis, force (F) and the resultant.

		MX	VX	ICVX	MY	VY	ICVY	MZ	VZ	ICVZ	MRES	VRES	ICVRES	MF	VF	ICVF
5 s	Grazing	48.3^{a}	3493^{a}	1.2^{c}	71.7^{a}	6821^{a}	1.0^{b}	33.4^{a}	1581^{c}	1.3^{b}	50.6^{a}	3987^{a}	0.8^{b}	48.9^{a}	2098^{a}	1.3^{c}
	Ruminating	17.7^{b}	753^{b}	1.4^{b}	45.7^{b}	4644^{b}	1.2^{b}	29.2^{b}	2965^{a}	1.3^{b}	29.6^{b}	3083^{b}	0.8^{b}	25.9^{b}	1095^{b}	1.7^{b}
	Other activities	7.0^{c}	353^{c}	4.4^{a}	14.0^{c}	1588^{c}	4.5^{a}	19.4^{c}	2345^{b}	3.8^{a}	11.8^{c}	1429^{c}	1.5^{a}	6.8^{c}	271^{c}	7.7^{a}
	P<	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
10 s	Grazing	47.8^{a}	3545^{a}	1.0^{b}	70.9^{a}	6868^{a}	0.9^{b}	33.4^{a}	1640^{c}	1.1^{b}	50.2^{a}	3978^{a}	0.8^{b}	48.8^{a}	2095^{a}	1.2^{b}
	Ruminating	15.8^{b}	624^{b}	1.1^{b}	44.6^{b}	4763^{b}	0.9^{b}	28.7^{b}	3226^{a}	0.9^{b}	28.4^{b}	3109^{b}	0.6^{c}	24.6^{b}	1078^{b}	0.5^{c}
	Other activities	4.5^{c}	198^{c}	3.1^{a}	10.6^{c}	1359^{c}	3.3^{a}	18.2^{c}	2592^{b}	2.7^{a}	9.2c	1311^{c}	1.1^{a}	3.6^{c}	126^{c}	4.4^{a}
	P<	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
30 s	Grazing	47.6^{a}	3625^{a}	0.8^{b}	70.6^{a}	6977^{a}	0.9^{b}	33.4^{a}	1695^{c}	0.9^{b}	50.0^{a}	4004^{a}	0.8^{a}	48.5^{a}	2101^{a}	1.2^{b}
	Ruminating	15.9^{b}	675^{b}	0.9^{b}	44.5^{b}	5066^{b}	0.8^{b}	28.6^{b}	3458^{a}	0.8^{b}	28.4^{b}	3178^{b}	0.6^{c}	24.5^{b}	1146^{b}	0.8^{b}
	Other activities	4.4^{c}	205^{c}	1.8^{a}	10.4^{c}	1431^{c}	1.9^{a}	18.1^{c}	2788^{b}	1.7^{a}	9.1^{c}	1327^{c}	0.7^{b}	3.5^{c}	137^{c}	2.2^{a}
	P<	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
60 s	Grazing	47.3^{a}	3645^{a}	0.8^{b}	70.2^{a}	7004^{a}	0.9^{b}	33.2^{a}	1697^{b}	0.8^{b}	49.7^{a}	3996^{a}	0.8^{a}	48.1^{a}	2090^{a}	1.1^{a}
	Ruminating	15.9^{b}	693^{b}	0.9^{b}	44.6^{b}	5177^{b}	0.8^{b}	28.7^{b}	3594^{a}	0.7^{c}	28.4^{b}	3212^{b}	0.5^{b}	24.6^{b}	1167^{b}	0.8^{b}
	Other activities	5.3^{c}	284^{c}	1.5^{a}	11.7^{c}	1590^{c}	1.3^{a}	18.5^{c}	2939^{a}	1.2^{a}	10.1^{c}	1415^{c}	0.5^{b}	4.8^{c}	221^{c}	1.1^{a}
	P<	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
120 s	Grazing	46.7^{a}	3630^{a}	0.8^{b}	69.9^{a}	7051^{a}	0.8^{ab}	33.1^{a}	1745^{b}	0.8^{a}	49.3^{a}	4004^{a}	0.01^{b}	47.5^{a}	2094^{a}	1.1^{a}
	Ruminating	16.4^{b}	762^{b}	0.8^{b}	44.0^{b}	5180^{b}	0.7^{b}	29.1^{b}	3722^{a}	0.6^{b}	28.5^{b}	3217^{b}	0.01^{b}	24.7^{b}	1181^{b}	0.8^{b}
	Other activities	6.2^{c}	356^{b}	1.2^{a}	13.8^{c}	1865^{c}	1.0^{a}	18.2^{c}	2875^{a}	0.8^{a}	11.1^{c}	1499^{c}	0.3^{a}	6.2^{c}	283^{c}	0.9^{b}
	P<	0.01	0.01	0.01	0.01	0.01	0.05	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
180 s	Grazing	46.2^{a}	3624^{a}	0.8^{b}	69.2^{a}	7017^{a}	0.8^{a}	33.0^{a}	1781^{b}	0.8^{a}	48.9^{a}	3993^{a}	0.8^{a}	47.4^{a}	2096^{a}	1.1^{a}
	Ruminating	16.4^{b}	785^{b}	0.8^{b}	43.2^{b}	5103^{b}	0.7^{b}	28.6^{a}	3707^{a}	0.6^{b}	28.2^{b}	3152^{b}	0.5^{b}	24.5^{b}	1172^{b}	0.8^{b}
	Other activities	8.9^{c}	568^{b}	0.9^{a}	18.9^{c}	2484^{c}	0.6^{b}	20.0^{b}	3013^{a}	0.7^{ab}	14.0^{c}	1783^{c}	0.4^{c}	8.2^{c}	382^{c}	0.7^{b}
	P<	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
300 s	Grazing	44.3^{a}	3457^{a}	0.8	68.2^{a}	7084^{a}	0.8^{a}	32.5^{a}	1862^{b}	0.8^{a}	47.5^{a}	3940^{a}	0.8^{a}	44.8^{a}	1964^{a}	1.1^{a}

Ruminating	17^{b}	887^{b}	0.7	43.8^{b}	5216^{b}	0.7^{b}	26.7^{b}	3467^{a}	0.5^{b}	28.1^{b}	3116^{b}	0.5^{b}	24.9^{b}	1229^{b}	0.8^{b}
Other activities	14.5^{b}	1119^{b}	0.8	22.6^{c}	2673^{c}	0.6^{b}	24.2^{b}	3253^{a}	0.6^{b}	18.5^{c}	2172^{c}	0.4^{c}	16.8^{b}	878^{b}	0.7^{b}
P<	0.01	0.01	ns	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Means followed by different letters differ significantly at $P < 0.05$.

Table 2. Allocation (expressed as percentage of the total) of the prevailing behavioural activity in the three classes of percentage considered for each epoch setting.

Epoch	50-75%	75-99%	100%	n
5 s	0.6	0.7	98.8	13995
10 s	1.8	1.0	97.4	6992
30 s	3.5	3.3	93.3	2334
60 s	4.5	6.6	88.3	1167
120 s	5.6	13.7	80.2	585
180 s	7.9	19.2	72.6	390
300 s	11.9	26.3	60.2	233

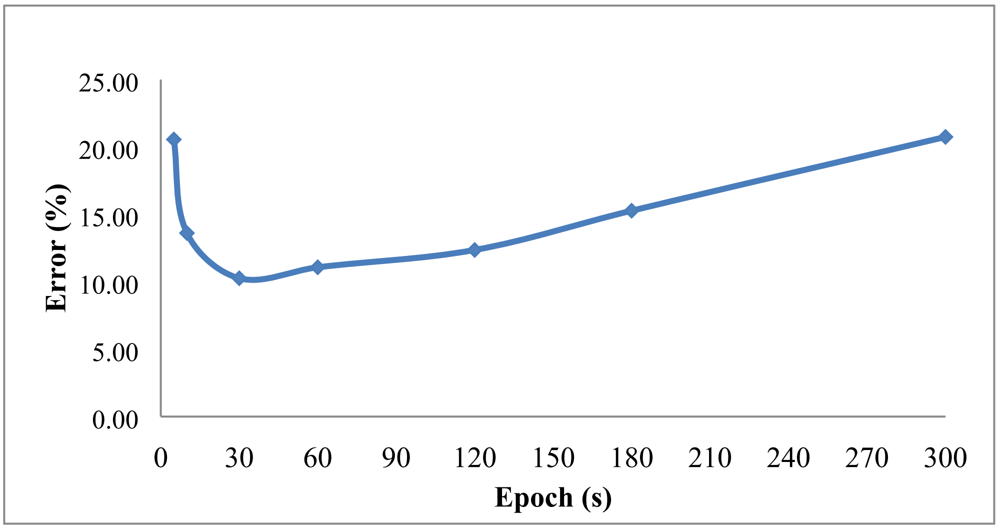

Figure 2. Distribution of errors in assignment of DA after bootstrap procedure among epoch settings

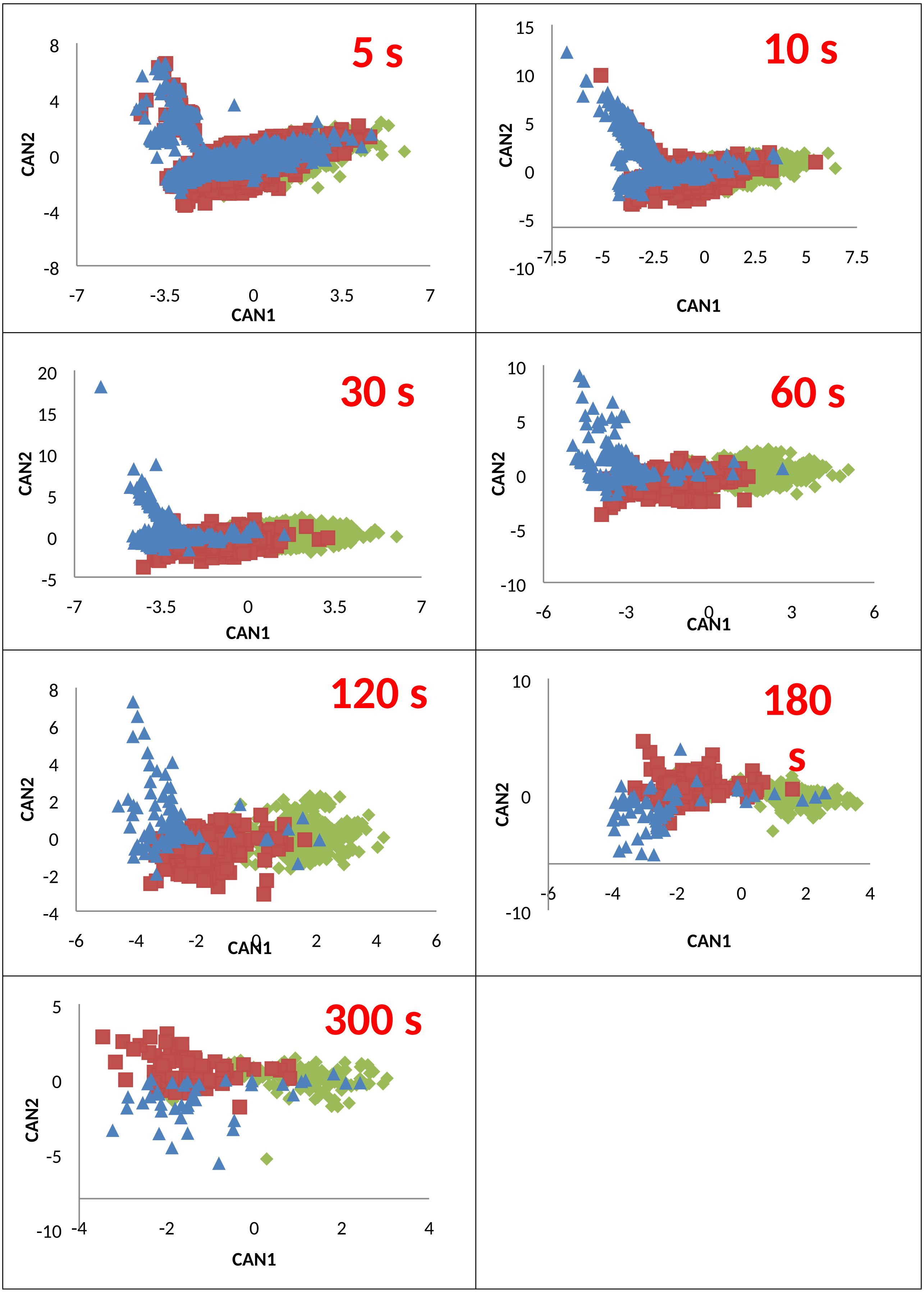

Figure 3. Plot of canonical variables (CAN 1, CAN 2) generated from discriminant analysis for different time epoch settings (5 s, 10 s, 30 s, 60 s, 120 s, 180 s, 300 s). ▲blue = other activities, ■ brown =ruminating, ♦ green =grazing.

Table 3. Variance explained (λ_1, λ_2) and standardized canonical coefficients at different time epoch settings.

	5 s		10 s		30 s		60 s		120 s		180 s		300 s	
	Can1	Can2	Can1	Can2	Can1	Can2	Can1	Can2	Can1	Can2	Can1	Can2	Can1	Can2
λ_1	0.88		0.91		0.93		0.93		0.93		0.88		0.78	
λ_2		0.12		0.08		0.07		0.07		0.07		0.12		0.22
Variables														
MX	0,52	-0,15	0,48	-0,72	0.36	-1.52	0.17	-1.95	-0,07	-2,45	-0,77	-1,78	0,34	-1,96
VX	0,35	0,98	0,57	1,52	0.59	2.29	0.60	2.78	0,81	3,14	0,99	2,98	0,83	2,93
ICVX	-0,05	0,23	-0,03	0,22	-0.09	0.59	-0.10	0.68	-0,05	0,52	0,02	0,72	-0,03	0,41
MY	0,95	0,57	1,29	0,55	1.15	1.03	0.82	1.61	0,86	1,66	0,62	3,28	1,44	2,66
VY	0,36	0,63	0,58	0,99	0.64	1.10	0.60	1.29	0,78	1,27	0,02	0,94	1,35	0,87
ICVY	-0,08	0,30	-0,03	0,18	0.02	-0.12	0.01	-0.05	0,02	-0,19	0,03	-0,29	0,22	0,63
MZ	0,92	0,87	1,49	0,86	1.98	1.09	2.33	1.21	2,35	1,06	2,04	1,49	2,08	1,57
VZ	-0,16	-0,03	-0,34	0,30	-0.87	0.37	-1.49	0.53	-1,38	0,55	-1,71	0,69	-0,58	0,41
ICVZ	-0,06	0,15	-0,03	0,06	-0.02	0.07	-0.03	0.11	0,02	0,02	-0,30	1,06	0,65	1,42
VRES	-1,64	-1,86	-2,41	-2,23	-2.26	-3.00	-1.82	-3.81	-2,02	-3,69	-0,82	-4,89	-3,46	-4,55
ICVRES	-0,002	-0,09	-0,24	0,49	-0.14	0.26	-0.04	-0.22	-0,08	0,17	0,50	-2,05	-1,30	-3,59
MF	0,81	-0,34	0,90	-0,54	0.98	-0.76	0.92	-0.95	0,65	-1,17	0,66	-0,26	0,88	0,70
VF	-0,02	0,52	0,09	0,65	0.01	0.90	-0.09	1.29	0,12	1,43	-0,16	1,26	0,06	0,88
ICVF	-0,13	0,64	-0,03	0,30	-0.003	0.22	0.001	0.35	0,01	0,29	-0,05	0,20	-0,11	0,09

Table 4. Mahalanobis distance from main behavioural activities at different time epoch settings.

			Ruminating	Other activities
Time epoch settings	5 s	Grazing	4	10
		Ruminating	0	3
		Other activities		0
	10 s	Grazing	7	17
		Ruminating	0	4
		Other activities		0
	30 s	Grazing	11	23
		Ruminating	0	5
		Other activities		0
	60 s	Grazing	12	24
		Ruminating	0	5
		Other activities		0
	120 s	Grazing	11	20
		Ruminating	0	4
		Other activities		0
	180 s	Grazing	10	17
		Ruminating	0	5
		Other activities		0
	300 s	Grazing	8	7
		Ruminating	0	4
		Other activities		0

Table 5. Performance of the model in the assignment of the behaviours at different time epoch settings.

		sensitivity	specificity	precision	accuracy	Cohen's k
		%	%	%	%	
Grazing	5 s	88.1	86.9	86.9	87.5	0.7
	10 s	94.7	90.8	91.9	92.8	0.8
	30 s	94.8	93.0	94.1	94.0	0.9
	60 s	95.0	92.9	94.0	94.0	0.9
	120 s	92.8	94.2	95.3	93.4	0.9
	180 s	91.6	92.4	93.6	91.9	0.9
	300 s	88.0	89.6	91.6	88.7	0.8
Ruminating	5 s	67.9	88.8	78.4	81.0	0.7
	10 s	73.5	93.9	86.8	86.7	0.8
	30 s	80.4	94.7	88.1	90.0	0.8
	60 s	79.8	93.9	86.3	89.4	0.8
	120 s	82.2	91.6	79.9	88.9	0.7
	180 s	78.3	90.2	76.9	86.7	0.7
	300 s	73.5	89.5	74.1	84.9	0.6
Other activities	5 s	79.6	92.0	59.6	90.4	0.5
	10 s	87.9	94.0	67.2	93.2	0.6
	30 s	92.3	96.0	77.9	95.5	0.7
	60 s	86.6	95.7	76.5	94.5	0.7
	120 s	79.2	95.5	75.9	93.0	0.7
	180 s	72.7	94.2	69.6	90.9	0.6
	300 s	57.0	89.7	48.9	84.9	0.4
Overall	5 s				79.4	0.7
	10 s				86.4	0.8
	30 s				89.7	0.8
	60 s				88.9	0.8
	120 s				87.6	0.8
	180 s				84.7	0.7
	300 s				79.3	0.6