

The effect of different time epoch settings on the classification of sheep behaviour using tri-axial accelerometry

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1 **The effect of different time epoch settings on the classification of sheep behaviour using tri-axial**  
2 **accelerometry**

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16

17 **Abstract**

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

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

38

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

40

## 41 **1. Introduction**

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

49 Accelerometers have been widely used to automatically detect and classify several behaviours in cattle, e.g.  
50 *oestrus* detection (Ueda *et al.*, 2011), walking (Robert *et al.*, 2009) feeding and standing activities in a free-  
51 stall barn (Arcidiacono *et al.*, 2017), sleeping posture (Fukasawa *et al.*, 2018) and time (Hokkanen *et al.*,  
52 2011), and eating, ruminating and resting **activities** (Watanabe *et al.*, 2008).

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

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

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

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

74 Optimizing the epoch setting, without compromising classification accuracy, could imply a number of  
75 advantages. Short epoch settings could increase the labour involved in processing data, deplete the memory  
76 device, decrease the battery duration and may also cause erroneous attribution activities during processing.

77 Actually, if an epoch shorter than the period of time an activity occurs is used, the number of false positive  
78 classifications for dynamic activities could increase probably due to transitioning between different activities  
79 or body shifts during static activities (Robert *et al.*, 2009). Conversely, optimized longer epoch settings  
80 might reduce the memory depletion and increase the battery duration without compromising the performance  
81 of the sensor. Nielsen, (2013) distinguished grazing from non-grazing behaviour with a 3D activity sensor  
82 that correctly classified the behaviours of dairy cows with a relatively high accuracy when the epoch was set  
83 at 5 s, 5 or 10 minutes. Other authors, as Vázquez Diosdado *et al.*, (2015), while classifying lying, standing  
84 and feeding behaviours in dairy cows, reported a small increase in the decision-tree classification algorithm

85 performance at the largest window size of 10 minutes if compared with 1 and 5 minutes epoch settings. In  
86 the present research, a customized tri-axial accelerometer based sensor, able to either store data in a micro  
87 SD card or send them to a remote computer, was used. In the future perspective of data pre-processing in the  
88 device itself, determining the optimum device settings before field application is crucial, because they could  
89 impact on monitoring system accuracy as well as on the effective battery and memory life.

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

96

## 97 **2. Materials and methods**

### 98 *2.1 Experimental site and animal management*

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

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

104 The study is part of an experiment conducted in spring 2016, from 1 March to 9 May, with 48 mature  
105 lactating Sarda dairy sheep that rotationally grazed berseem clover (*Trifolium alexandrinum* L.) and Italian  
106 ryegrass (*Lolium multiflorum* Lam.) for 6 hours day<sup>-1</sup>. Two grazing treatments were used: a mixture of  
107 berseem clover and Italian ryegrass, and two monocultures (berseem clover and ryegrass) grazed in  
108 succession. In the latter case, the sheep grazed the first 3 hours on the clover and the last 3 hours on the  
109 ryegrass. The ewes were machine milked twice daily at 0700 hours and 1500 hours. During milkings, they  
110 were individually fed in the milking parlour with commercial concentrate (500 g ewe<sup>-1</sup> day) split into two  
111 meals. In the remaining daytime, the animals were kept indoors and group-fed 500 g ewe<sup>-1</sup> of ryegrass hay  
112 and 300 g ewe<sup>-1</sup> of alfalfa hay in separate troughs. On four occasions (test days) during the experiment, eight

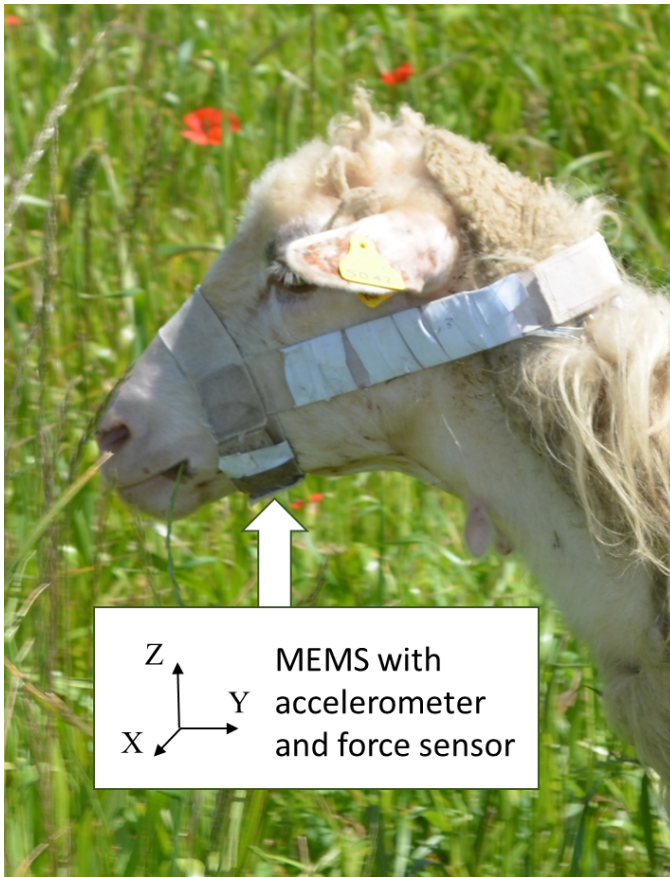
113 ewes (four per treatment), with an age of  $3.1 \pm 1.6$  years (mean  $\pm$  standard deviation), live weight of  $41.3 \pm 2.8$   
114 kg, lactation stage of  $73 \pm 6$  days in milk and milk yield of  $2062 \pm 362$  g ewe<sup>-1</sup> day<sup>-1</sup>, were used. On each test  
115 day, after the morning milking, the ewes were carried on a trailer to the experimental plots and equipped  
116 with the BEHARUM device before the six hours of access to pasture. At the end of the grazing session, the  
117 BEHARUM devices were removed from the animals.

118

## 119 *2.2 Description of the BEHARUM device and feeding behaviour recording*

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

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



131

132

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

135

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

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

145

146 *2.3 Preliminary data processing*

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

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

169

## 170 2.4 Data processing

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

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

$$181 \text{ CAN} = c_1X_1 + c_2X_2 + \dots + c_nX_n$$

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

186 The distance between groups was evaluated by using the Mahalanobis' distance, whereas the effective  
187 groups' separation was tested by using the corresponding Hotelling's T-square test (De Maesschalck *et al.*,  
188 2000). DA was then **used** to classify epochs into one of the three behaviours (Mardia *et al.*, 2000).

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

$$195 \text{ Sensitivity} = \text{TP}/(\text{TP}+\text{FN});$$

$$196 \text{ Specificity} = \text{TN}/(\text{TN}+\text{FP});$$

$$197 \text{ Precision} = \text{TP}/(\text{TP}+\text{FP});$$

$$198 \text{ Accuracy} = (\text{TP}+\text{TN})/(\text{TP}+\text{TN}+\text{FP}+\text{FN})$$

199 Where TP, TN, FP and FN are true positive, true negative, false positive and false negative counts  
200 respectively. The Coehn's  $k$  coefficient was calculated (Fleiss, 1981) to evaluate the agreement between

201 observed and model predicted corrected for agreement that would be expected by chance, both for each  
202 behaviour and overall. The k values were judged according to the criteria of Landis and Koch (1977).

203

### 204 3. Results

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

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

213

#### 214 3.1 Discrimination between behaviour activities

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

220 In developing multivariate techniques, the MRES variable was discarded from the analysis because it made  
221 the (co)variance matrix singular due to linear dependencies with other variables. The CDA significantly  
222 discriminated between the three behaviours (Hotelling's test  $P < 0.0001$ ) by extracting two canonical  
223 functions for each epoch set. The variation  $\lambda_1$  accounted for CAN1, ranged among epochs between 0.78 and  
224 0.93 whether the variation  $\lambda_2$  explained by CAN2 ranged between 0.08 and 0.22 (Table 3).

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

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

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

235

### 236 *3.2 Performance of the discriminant analysis model*

237 The performances of the DA model, displayed in Table 5, show that the sensitivity of the model to predict  
238 grazing was the highest in the 60 s epoch set and the specificity in the 120 s epoch set. When the model was  
239 used to predict the rumination, the specificity reached the maximum value in the 30 s setting whereas the  
240 sensitivity in the 120 s epoch setting. The 30 s epoch length was the best to predict other activities, both in  
241 terms of sensitivity and specificity. The highest precision of the models to predict grazing was recorded in  
242 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-  
243 and 180 s. Ruminating and other activities behaviours were predicted with the highest precision and accuracy  
244 in the 30 s epoch with a k value of 0.8 and 0.7, respectively.

245 The overall accuracy values of the prediction models were similar in the range between 10 s and 120 s  
246 epochs, peaking in the 30 s epoch. The Coehn's k coefficient reached a plateau value (0.8) in the 10-, 30-,  
247 60- and 120 s epochs.

248

## 249 **4. Discussions**

### 250 *4.1 Discrimination between behaviour activities*

251 In this study a multivariate statistical algorithm was developed, by using tri-axial acceleration data obtained  
252 from an under lower jaw mounted sensor, to classify grazing, ruminating and other activities of dairy sheep.  
253 The CDA successfully distinguished the different behaviours, although the CAN1 vs CAN2 scatter plots  
254 (Figure 3) showed different levels of separation according to the time epoch length. This fact could be due to

255 the variation ( $\lambda_1$ ) explained by CAN1 that reached higher values in 30-, 60-, and 120 s than in the other time  
256 epochs (Table 3), whereas CAN2 was not able to separate behaviours (Figure 3).

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

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

279 In CAN2, which explained a very low part of the total variation ( $0.08 < \lambda_2 < 0.22$ ), VRES showed the  
280 highest standardized canonical coefficient at all epochs, in agreement with what reported by Giovanetti *et al.*,  
281 (2017a) who used BEHARUM device to monitor the feeding behaviour of dairy sheep, using a 60 s time

282 epoch. The importance of these variables in discriminating sheep behaviours was also reported by Barwick *et*  
283 *al.*, (2018).

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

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

301

#### 302 4.2 Performance of the discriminant analysis model

303 The performance of the model changed according to the predicted behaviour (Table 5). In fact, the grazing  
304 activity showed best performance, in terms of sensitivity and precision, than the other two activities for  
305 almost all the epoch set, thus confirming the results of other studies (Giovanetti *et al.*, 2017a; Nadimi *et al.*,  
306 2012). This is probably due to the higher correct true positive classification of grazing than ruminating and  
307 other activities, indicating that the classifier had problems predicting positive cases correctly in the last two  
308 classes that became most easily confused with other behaviours.

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

315 Grazing behaviour was predicted in 5 s epoch dataset with higher sensitivity (88.1% vs 84.3%) but lower  
316 specificity (86.9% vs 97.3%) and precision (86.9% vs 92.9%) than in the work by Alvarenga *et al.*, (2016)  
317 on Merino ewes. The precision in the current study resulted anyway higher than that found by Marais *et al.*,  
318 (2014) using a 5.12 s epoch, which was c.a. 66%. The 10 s epoch length, conversely, showed higher  
319 sensitivity (94.7% vs 91.7%) and precision (91.9% vs 89.8%) but lower specificity (90.8% vs 96.2%) in  
320 comparison with data by Alvarenga *et al.*, (2016). Barwick *et al.*, (2018) with the same epoch setting of 10 s  
321 found different performances in discriminating sheep grazing behaviour according to deployment position  
322 (ear, collar, leg). They actually reported the best performance in ear deployment that produced better results  
323 than our study, apart from sensitivity (92.0 vs 94.7%). Rodriguez *et al.* (2017), in an experiment with sheep,  
324 dividing their dataset in epochs of 14 s, reported performance similar to our 10 s epoch for grazing behaviour  
325 recognition. They actually found a sensitivity of 91.3%, a precision of 90.9%, a specificity of 91.9% and an  
326 accuracy of 91.6%. Moreau *et al.*, (2009), even if in a study conducted with grazing goats wearing the  
327 Hobo® G Pendant Data Logger, reported a true recognition rate of eating behaviour (grazing or browsing)  
328 similar to our results for 5 (89% vs 87% respectively) and 10 s (91% vs 92% respectively).

329 We encountered some difficulties in comparing the performance of the BEHARUM device for epochs larger  
330 than 20 s with the literature, since few papers regarding the use of accelerometer sensor in small ruminants  
331 have been published. Moreover, a comparison of results obtained in sheep with those obtained with large  
332 animals could not be appropriate. This assumption is supported by the results observed in a study conducted  
333 with the BEHARUM device placed under the jaw of cattle at pasture. Giovanetti *et al.*, (2017b), using the  
334 same device (BEHARUM), time epoch setting and statistical data analysis as in the present experiment,  
335 found that overall accuracy of 5, 10 and 30 s epochs in sheep showed higher values than those reported in

336 cattle (79.4%, 86.4% and 89.7%, vs 77.5%, 82.2% and 88.8% in sheep and cattle, respectively). This was  
337 probably due to the better capability of the model, for those epochs, to predict grazing activity in sheep than  
338 cattle.

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

347 Looking towards the 60 s epoch we can observe a slightly lower overall accuracy (88.9% vs 93.0%) and  
348 Coehn's k coefficient (0.8 vs 0.9) than those found by Giovanetti *et al.*, (2017a) and this may be due to the  
349 bigger and more varied dataset utilized in this paper than in the previous study. As a matter of fact, in the  
350 present research sheep grazed mixed grass and legume pastures whereas, in the work by Giovanetti *et al.*,  
351 (2017a), animals were fed on pasture monocultures only.

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

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

362

363 **5. Conclusions**

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

371

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377

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- 459

460 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  
 461 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 <sup>a</sup>	3493 <sup>a</sup>	1.2 <sup>c</sup>	71.7 <sup>a</sup>	6821 <sup>a</sup>	1.0 <sup>b</sup>	33.4 <sup>a</sup>	1581 <sup>c</sup>	1.3 <sup>b</sup>	50.6 <sup>a</sup>	3987 <sup>a</sup>	0.8 <sup>b</sup>	48.9 <sup>a</sup>	2098 <sup>a</sup>	1.3 <sup>c</sup>
	Ruminating	17.7 <sup>b</sup>	753 <sup>b</sup>	1.4 <sup>b</sup>	45.7 <sup>b</sup>	4644 <sup>b</sup>	1.2 <sup>b</sup>	29.2 <sup>b</sup>	2965 <sup>a</sup>	1.3 <sup>b</sup>	29.6 <sup>b</sup>	3083 <sup>b</sup>	0.8 <sup>b</sup>	25.9 <sup>b</sup>	1095 <sup>b</sup>	1.7 <sup>b</sup>
	Other activities	7.0 <sup>c</sup>	353 <sup>c</sup>	4.4 <sup>a</sup>	14.0 <sup>c</sup>	1588 <sup>c</sup>	4.5 <sup>a</sup>	19.4 <sup>c</sup>	2345 <sup>b</sup>	3.8 <sup>a</sup>	11.8 <sup>c</sup>	1429 <sup>c</sup>	1.5 <sup>a</sup>	6.8 <sup>c</sup>	271 <sup>c</sup>	7.7 <sup>a</sup>
	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 <sup>a</sup>	3545 <sup>a</sup>	1.0 <sup>b</sup>	70.9 <sup>a</sup>	6868 <sup>a</sup>	0.9 <sup>b</sup>	33.4 <sup>a</sup>	1640 <sup>c</sup>	1.1 <sup>b</sup>	50.2 <sup>a</sup>	3978 <sup>a</sup>	0.8 <sup>b</sup>	48.8 <sup>a</sup>	2095 <sup>a</sup>	1.2 <sup>b</sup>
	Ruminating	15.8 <sup>b</sup>	624 <sup>b</sup>	1.1 <sup>b</sup>	44.6 <sup>b</sup>	4763 <sup>b</sup>	0.9 <sup>b</sup>	28.7 <sup>b</sup>	3226 <sup>a</sup>	0.9 <sup>b</sup>	28.4 <sup>b</sup>	3109 <sup>b</sup>	0.6 <sup>c</sup>	24.6 <sup>b</sup>	1078 <sup>b</sup>	0.5 <sup>c</sup>
	Other activities	4.5 <sup>c</sup>	198 <sup>c</sup>	3.1 <sup>a</sup>	10.6 <sup>c</sup>	1359 <sup>c</sup>	3.3 <sup>a</sup>	18.2 <sup>c</sup>	2592 <sup>b</sup>	2.7 <sup>a</sup>	9.2 <sup>c</sup>	1311 <sup>c</sup>	1.1 <sup>a</sup>	3.6 <sup>c</sup>	126 <sup>c</sup>	4.4 <sup>a</sup>
	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 <sup>a</sup>	3625 <sup>a</sup>	0.8 <sup>b</sup>	70.6 <sup>a</sup>	6977 <sup>a</sup>	0.9 <sup>b</sup>	33.4 <sup>a</sup>	1695 <sup>c</sup>	0.9 <sup>b</sup>	50.0 <sup>a</sup>	4004 <sup>a</sup>	0.8 <sup>a</sup>	48.5 <sup>a</sup>	2101 <sup>a</sup>	1.2 <sup>b</sup>
	Ruminating	15.9 <sup>b</sup>	675 <sup>b</sup>	0.9 <sup>b</sup>	44.5 <sup>b</sup>	5066 <sup>b</sup>	0.8 <sup>b</sup>	28.6 <sup>b</sup>	3458 <sup>a</sup>	0.8 <sup>b</sup>	28.4 <sup>b</sup>	3178 <sup>b</sup>	0.6 <sup>c</sup>	24.5 <sup>b</sup>	1146 <sup>b</sup>	0.8 <sup>b</sup>
	Other activities	4.4 <sup>c</sup>	205 <sup>c</sup>	1.8 <sup>a</sup>	10.4 <sup>c</sup>	1431 <sup>c</sup>	1.9 <sup>a</sup>	18.1 <sup>c</sup>	2788 <sup>b</sup>	1.7 <sup>a</sup>	9.1 <sup>c</sup>	1327 <sup>c</sup>	0.7 <sup>b</sup>	3.5 <sup>c</sup>	137 <sup>c</sup>	2.2 <sup>a</sup>
	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 <sup>a</sup>	3645 <sup>a</sup>	0.8 <sup>b</sup>	70.2 <sup>a</sup>	7004 <sup>a</sup>	0.9 <sup>b</sup>	33.2 <sup>a</sup>	1697 <sup>b</sup>	0.8 <sup>b</sup>	49.7 <sup>a</sup>	3996 <sup>a</sup>	0.8 <sup>a</sup>	48.1 <sup>a</sup>	2090 <sup>a</sup>	1.1 <sup>a</sup>
	Ruminating	15.9 <sup>b</sup>	693 <sup>b</sup>	0.9 <sup>b</sup>	44.6 <sup>b</sup>	5177 <sup>b</sup>	0.8 <sup>b</sup>	28.7 <sup>b</sup>	3594 <sup>a</sup>	0.7 <sup>c</sup>	28.4 <sup>b</sup>	3212 <sup>b</sup>	0.5 <sup>b</sup>	24.6 <sup>b</sup>	1167 <sup>b</sup>	0.8 <sup>b</sup>
	Other activities	5.3 <sup>c</sup>	284 <sup>c</sup>	1.5 <sup>a</sup>	11.7 <sup>c</sup>	1590 <sup>c</sup>	1.3 <sup>a</sup>	18.5 <sup>c</sup>	2939 <sup>a</sup>	1.2 <sup>a</sup>	10.1 <sup>c</sup>	1415 <sup>c</sup>	0.5 <sup>b</sup>	4.8 <sup>c</sup>	221 <sup>c</sup>	1.1 <sup>a</sup>
	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 <sup>a</sup>	3630 <sup>a</sup>	0.8 <sup>b</sup>	69.9 <sup>a</sup>	7051 <sup>a</sup>	0.8 <sup>ab</sup>	33.1 <sup>a</sup>	1745 <sup>b</sup>	0.8 <sup>a</sup>	49.3 <sup>a</sup>	4004 <sup>a</sup>	0.01 <sup>b</sup>	47.5 <sup>a</sup>	2094 <sup>a</sup>	1.1 <sup>a</sup>
	Ruminating	16.4 <sup>b</sup>	762 <sup>b</sup>	0.8 <sup>b</sup>	44.0 <sup>b</sup>	5180 <sup>b</sup>	0.7 <sup>b</sup>	29.1 <sup>b</sup>	3722 <sup>a</sup>	0.6 <sup>b</sup>	28.5 <sup>b</sup>	3217 <sup>b</sup>	0.01 <sup>b</sup>	24.7 <sup>b</sup>	1181 <sup>b</sup>	0.8 <sup>b</sup>
	Other activities	6.2 <sup>c</sup>	356 <sup>b</sup>	1.2 <sup>a</sup>	13.8 <sup>c</sup>	1865 <sup>c</sup>	1.0 <sup>a</sup>	18.2 <sup>c</sup>	2875 <sup>a</sup>	0.8 <sup>a</sup>	11.1 <sup>c</sup>	1499 <sup>c</sup>	0.3 <sup>a</sup>	6.2 <sup>c</sup>	283 <sup>c</sup>	0.9 <sup>b</sup>
	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 <sup>a</sup>	3624 <sup>a</sup>	0.8 <sup>b</sup>	69.2 <sup>a</sup>	7017 <sup>a</sup>	0.8 <sup>a</sup>	33.0 <sup>a</sup>	1781 <sup>b</sup>	0.8 <sup>a</sup>	48.9 <sup>a</sup>	3993 <sup>a</sup>	0.8 <sup>a</sup>	47.4 <sup>a</sup>	2096 <sup>a</sup>	1.1 <sup>a</sup>
	Ruminating	16.4 <sup>b</sup>	785 <sup>b</sup>	0.8 <sup>b</sup>	43.2 <sup>b</sup>	5103 <sup>b</sup>	0.7 <sup>b</sup>	28.6 <sup>a</sup>	3707 <sup>a</sup>	0.6 <sup>b</sup>	28.2 <sup>b</sup>	3152 <sup>b</sup>	0.5 <sup>b</sup>	24.5 <sup>b</sup>	1172 <sup>b</sup>	0.8 <sup>b</sup>
	Other activities	8.9 <sup>c</sup>	568 <sup>b</sup>	0.9 <sup>a</sup>	18.9 <sup>c</sup>	2484 <sup>c</sup>	0.6 <sup>b</sup>	20.0 <sup>b</sup>	3013 <sup>a</sup>	0.7 <sup>ab</sup>	14.0 <sup>c</sup>	1783 <sup>c</sup>	0.4 <sup>c</sup>	8.2 <sup>c</sup>	382 <sup>c</sup>	0.7 <sup>b</sup>
	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 <sup>a</sup>	3457 <sup>a</sup>	0.8	68.2 <sup>a</sup>	7084 <sup>a</sup>	0.8 <sup>a</sup>	32.5 <sup>a</sup>	1862 <sup>b</sup>	0.8 <sup>a</sup>	47.5 <sup>a</sup>	3940 <sup>a</sup>	0.8 <sup>a</sup>	44.8 <sup>a</sup>	1964 <sup>a</sup>	1.1 <sup>a</sup>

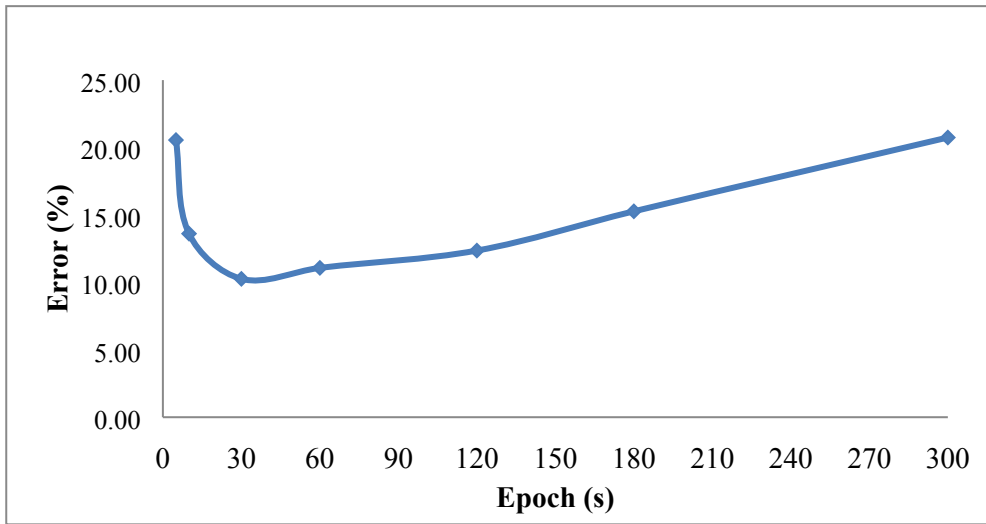
Ruminating	17 <sup>b</sup>	887 <sup>b</sup>	0.7	43.8 <sup>b</sup>	5216 <sup>b</sup>	0.7 <sup>b</sup>	26.7 <sup>b</sup>	3467 <sup>a</sup>	0.5 <sup>b</sup>	28.1 <sup>b</sup>	3116 <sup>b</sup>	0.5 <sup>b</sup>	24.9 <sup>b</sup>	1229 <sup>b</sup>	0.8 <sup>b</sup>
Other activities	14.5 <sup>b</sup>	1119 <sup>b</sup>	0.8	22.6 <sup>c</sup>	2673 <sup>c</sup>	0.6 <sup>b</sup>	24.2 <sup>b</sup>	3253 <sup>a</sup>	0.6 <sup>b</sup>	18.5 <sup>c</sup>	2172 <sup>c</sup>	0.4 <sup>c</sup>	16.8 <sup>b</sup>	878 <sup>b</sup>	0.7 <sup>b</sup>
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

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

463 **Table 2.** Allocation (expressed as percentage of the total) of the prevailing behavioural activity in the three  
464 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

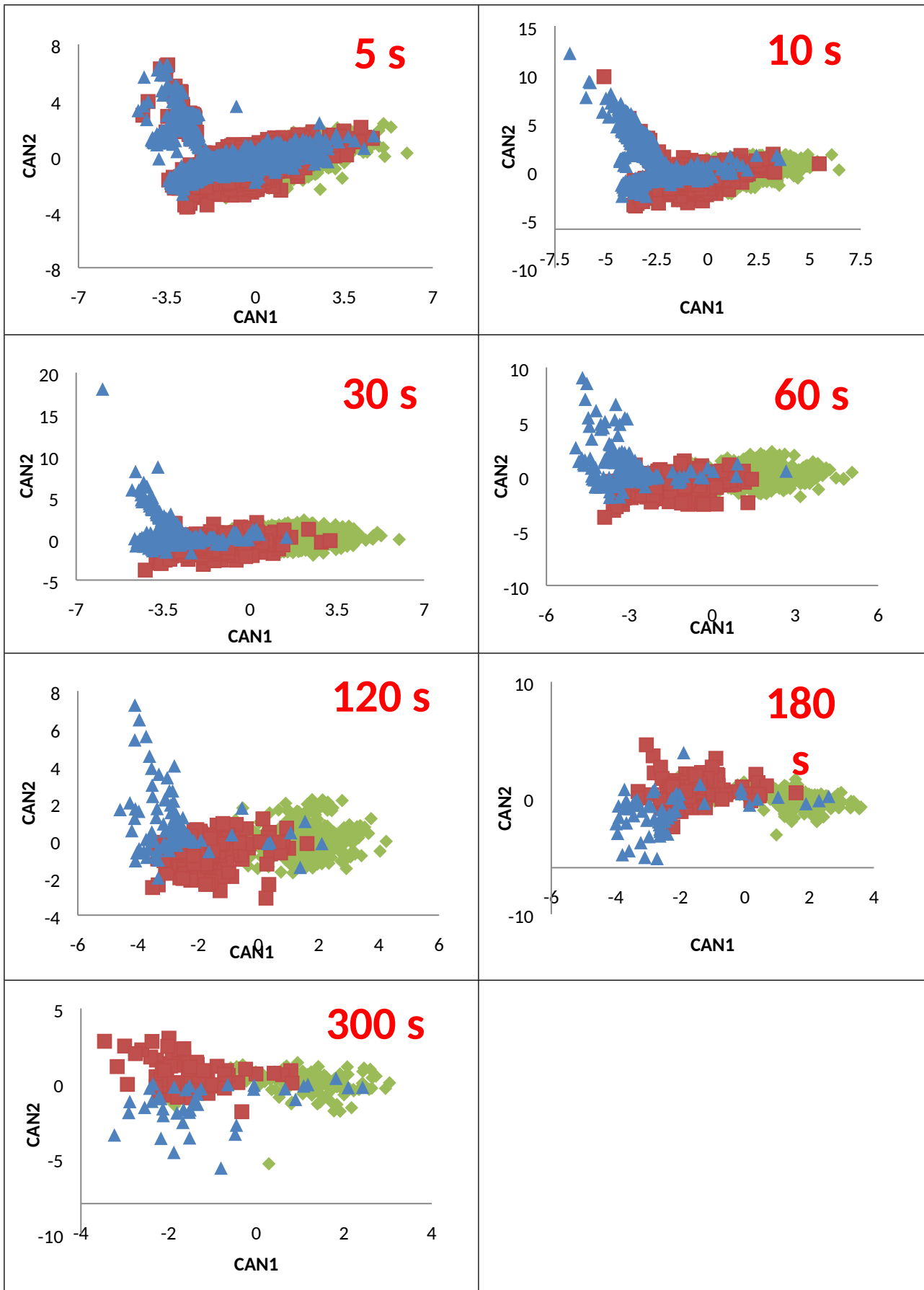
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467 **Figure 2.** Distribution of errors in assignment of DA after bootstrap procedure among epoch settings

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

472 **Table 3.** Variance explained ( $\lambda_1, \lambda_2$ ) 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
$\lambda_1$	0.88		0.91		0.93		0.93		0.93		0.88		0.78	
$\lambda_2$		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

474 **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

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477 **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