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Evaluation of proper sensor position for classification of sheep behaviour through accelerometers.

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Abstract

Automated classification and identification of feeding behaviour through sensors, has the potential to allow improvements in animal health and welfare. Sensor position, as well as epoch setting of segmented signal data, affects classification accuracy in behavioural activity discrimination. The aim of this study was to evaluate the effects of position, at different time epoch setting, of a tri-axial accelerometer based device (BEHARUM) on the classification of behaviour types such as grazing, ruminating and other activities in sheep grazing a chicory-based sward. Sheep were video recorded, during accelerometer deployment, by fixed camera. Mean, variance and inverse coefficient of variation (i.e. mean/ standard deviation), of the raw acceleration data for each axis, as well as the resultant variance and inverse coefficient of variation values of the three axes, were calculated for the following positions: mouth, nape, collar and epoch settings: 5s, 10s, 30s, 60s, 120s, 180s, 300s. Video recordings were coded manually assigning to each position and epoch the prevailing behaviour. Multivariate discriminant analysis (DA) was used to distinguish between the three behaviour types. To evaluate the performance of DA in discriminating the three activities, overall accuracy and Coehn's k coefficient were calculated, based on the error distribution in assignment. Mouth position recorded the highest accuracies and Coehn's k coefficient in 300 seconds time epoch setting (88% and 0.8 respectively), as well as collar position (90% and 0.8 respectively), while nape position showed the best performance in 180 and 300 seconds (80% and 0.6 respectively). Overall, the best performance of DA was obtained using collar position in particular at 300s time epoch.

Keywords: discriminant analysis, feeding behaviour, accelerometer, dairy sheep

1. Introduction

Feeding behaviour could be considered as the whole process by which the animal ingests the feed in order to match their nutrient requirements. Grazing and ruminating are the most important daily behaviour types for ruminants in terms of time allocation. Monitoring these behaviours of free-ranging ruminants is an effective way to understand pasture-animal interface relationships, to better manage grassland systems (Coates and Penning, 2000) as well as to assess animal health and welfare (Walton et al., 2018).

Embedded and wearable devices encompassing tri-axial accelerometers are currently used to classify and monitor changes in ruminant feeding activity (Van Hertem et al., 2013; Vázquez Diosdado et al., 2015; Mattachini et al., 2016). Some studies classifying feeding behaviour of sheep reported high classification accuracy through these devices (>90%) (Umstätter et al., 2008; McLennan et al., 2015; Alvarenga et al., 2016; Giovanetti et al., 2017a; Decandia et al., 2018).

However, there are various factors, such as sensor position, sampling frequency, window sizes etc that can affect performance of behavioural classification using accelerometers.

There have been a number of studies that have deployed accelerometer sensors on small ruminants, which have often used either leg, collar or halter mounting positions. Marais et al. (2014) attaching accelerometers around the neck of sheep identified grazing behaviour with low accuracy, probably because of the position chosen to attach the accelerometer. Moreau et al. (2009) observed that, in goats fed at pasture, the accelerometers placed at the withers were able to detect satisfactorily the head position (up or down), but when the sensor was fixed to the neck, it seemed even more effective in detecting feeding behaviour. Mason and Sneddon (2013) evaluated a sensor placed near the head/neck of sheep grazing predominantly ryegrass pasture and found promising results in distinguish grazing versus simply standing. Nadimi et al. (2011) used a two-axis accelerometer placed at the nape of sheep at pasture in order to observe the position of the head (down or up) and reported that this device was able to identify the head movements successfully. Giovanetti et al., (2017a) found good results in feeding activity classification with accelerometer sensor placed in a muzzle, also obtaining a good estimation of the number of bites. Whilst these deployments may be acceptable in a research context, from a commercial perspective, the most applicable, industry acceptable, standard is an eartag or a collar that aligns with conventional husbandry practices.

Another factor considered on the classification of behaviour is the use of epochs, which groups data over a predetermined time period (Robert et al., 2009; Yoshitoshi et al., 2013; Decandia et al., 2018).

These calculated epoch values are assumed to be representative of the estimated intensity of activities measured during the set time period. The choice of the epoch duration is linked to the type of animal behavior. Usually short epochs may be preferable when the animal shifts between behavioural activity types rapidly, as found in grazing sheep by some authors (Alvarenga et al., 2016; Decandia et al., 2018), whereas an opposite selection (longer epochs) is suitable in grazing beef cattle shifting slowly between activities (Giovanetti et al., 2017b). The choice of longer epochs can offer the advantage of data-smoothing through time averaging, while the disadvantage is a higher proportion of mixture of two or more activities of varying intensity, resulting in the data average reflecting an intermediate intensity (Barwich et al., 2020). In a previous work using an accelerometer sensor in grazing sheep, 30-60-s sample window recorded the best accuracy to classify grazing, ruminating and other activities (Decandia et al., 2018). To develop a real world's practical and useful solution, it is important to evaluate various positions for sensors, as well as the most energy efficient way of sampling and processing the data (i.e., choosing the sampling rate and size of the time window for feature extraction). To address these challenges, a study was performed to evaluate the effect of position (mouth, nape and collar) with different time epoch settings (5, 10, 30, 60, 120, 180 and 300s) of a tri-axial accelerometer based device on the classification of behavioural types such as grazing, ruminating and other activities in grazing dairy sheep.

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, 32m a.s.l). The animal protocol described below 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 was conducted in the first two weeks of May 2019. Three milking adult Sarda ewes, 3.5 ± 0.8 years old (mean ± standard deviation), live weight of 43.5 ± 1.5 kg, body condition score of 2.5 ± 0.2, lactation stage of 83 ± 18 days in milk, and milk yield of 1,200 ± 120 g ewe^{-1} day^{-1} were used.

The ewes were machine milked twice daily at 0700 h and 1500 h. During milking, animals were individually fed in the milking parlour with commercial concentrate (400 g ewe^{-1} day^{-1}) split into two meals. In the first week, the ewes were accustomed to graze, from 0830 to 1430 h, one experimental plot (250 m^2) sown with a monoculture of chicory (*Cichorium intybus* L.). In the remaining daytime, the animals were kept indoors and group-fed ryegrass hay *ad libitum*.

In the second week of May, on three occasions (test days) after the morning milking, the ewes were carted on a trailer to the experimental plot and equipped with the accelerometer devices (see description in the next paragraph) before the access to pasture. At the end of the grazing session, the ewes were carted back to the milking machine and afterward to the stall where, at 1700 h, the devices were removed. To facilitate individual identification, sheep were numbered with coloured livestock spray on both flanks.

2.2 Description of the accelerometer based device (BEHARUM) and feeding behaviour recording

The BEHARUM device (Giovanetti et al., 2017a) includes a tri-axial accelerometer sensor, inserted in a micro-electromechanical compact system (MEMS) with on-board peripherals, that samples raw accelerations at a frequency of 62.5 Hz and converts 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. The converted data could be sent (via 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. A software package (DAS Client, Electronic System) was installed on the computer to activate or deactivate the BEHARUM device and manage data acquisition. In this experiment, we adopted the recording of acceleration and force data on micro SD card.

On each test day, the 3 experimental ewes were equipped each with 3 BEHARUM devices placed in 3 different positions (mouth, nape and collar, Figure 1). In mouth position the BEHARUM, inserted in a halter, was placed under the lower jaw of the sheep; in nape position the BEHARUM was fixed in the back part of the halter behind the head; in collar position the BEHARUM was inserted in a traditional brazen bell without clapper, hang in a lightweight leather tie.

A video camera (Sanyo Xacti VPC-TH1, Sanyo Electric Co., Ltd. OSAKA, Japan) was fixed to the tripod and positioned in a corner outside of the field in order to record the feeding behaviour of sheep, one at a time, equipped with the accelerometer sensors during accelerometer deployment. Video recordings of each animal lasted 20–25 min. The internal clock of the camera as well as the internal clock of the computer were both synced with the website (https://time.is) prior to deployment. This ensured both the camera and accelerometers were synchronized in time to allow accurate annotation of the accelerometer data after behavioural recordings were made.

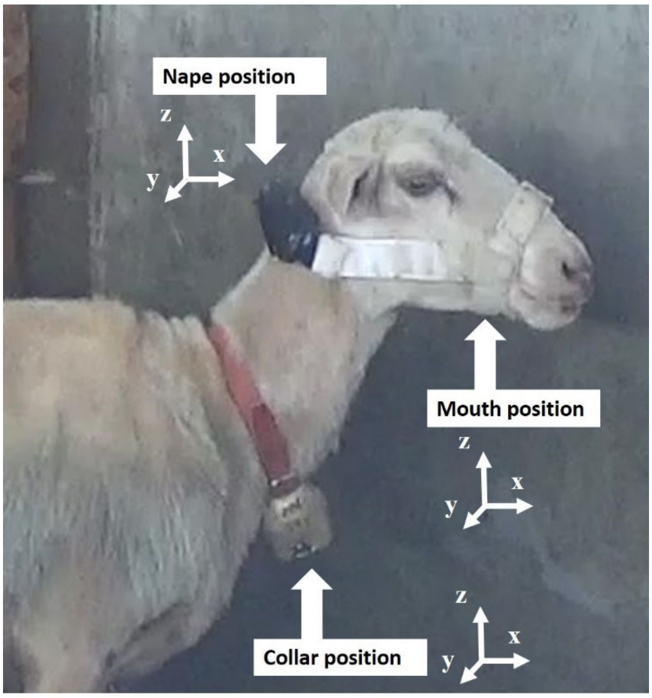


Figure 1. BEHARUM devices placed in 3 different positions (mouth, nape and collar).

2.3. Data pre-processing

On the basis of the collected videos, for each position, a file including the three acceleration values recorded every second for each axis and one of the three behavioural activities (grazing, ruminating, and other activities) accomplished by the animal per second was created. We obtained a total of 96,395, 102,746, and 80,370 records per mouth, nape and collar position respectively. 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), variance (VX, VY, VZ), inverse coefficient of variation (i.e. mean/ standard deviation, ICVX, ICVY, ICVZ), of acceleration data for each axis, as well as the resultant mean (MRES), variance (VRES) and ICV (ICVRES) values of the three axes (Watanabe et al., 2008), were calculated for the following epoch settings: 5s, 10s, 30s, 60s, 120s, 180s, 300s. The mean and standard deviation of these variables for each experimental animal, each position and each epoch are reported in supplementary materials. 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. For each epoch setting, data were arranged in a multivariate manner with fifteen columns including the epoch, the prevailing activity and the thirteen acceleration variables (MX, MY, MZ, VX, VY, VZ, ICVX, ICVY, ICVZ, MRES, VRES, ICVRES). Eventually, we obtained twenty-one datasets, seven for each sensor position and, within position, one for each epoch setting under study.

2.4. Data processing

The twenty-one datasets were 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 thirteen acceleration 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:

$$CAN = c_1X_1 + c_2X_2 + ...+c_nX_n$$

where c_i are the canonical coefficients (CC) and X_i are 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, a metric specifically developed to calculate distances in a multivariate space that assigns different weights to correlated variables. The effective groups' separation was then tested by using the 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, precision, sensitivity (also known as recall), F-score, specificity and accuracy were computed, based on the error distribution in assignment, using the following equations:

Precision = $\frac{\mathrm{TP}}{\mathrm{TP+FP}}$;

Sensitivity = $\frac{\mathrm{TP}}{\mathrm{TP+FN}}$;

F-Score = 2 x $\frac{\text{Precision x Sensitivity}}{\text{Precision+Sensitivity}}$;

Specificity = $\frac{\mathrm{TN}}{\mathrm{TN+FP}}$;

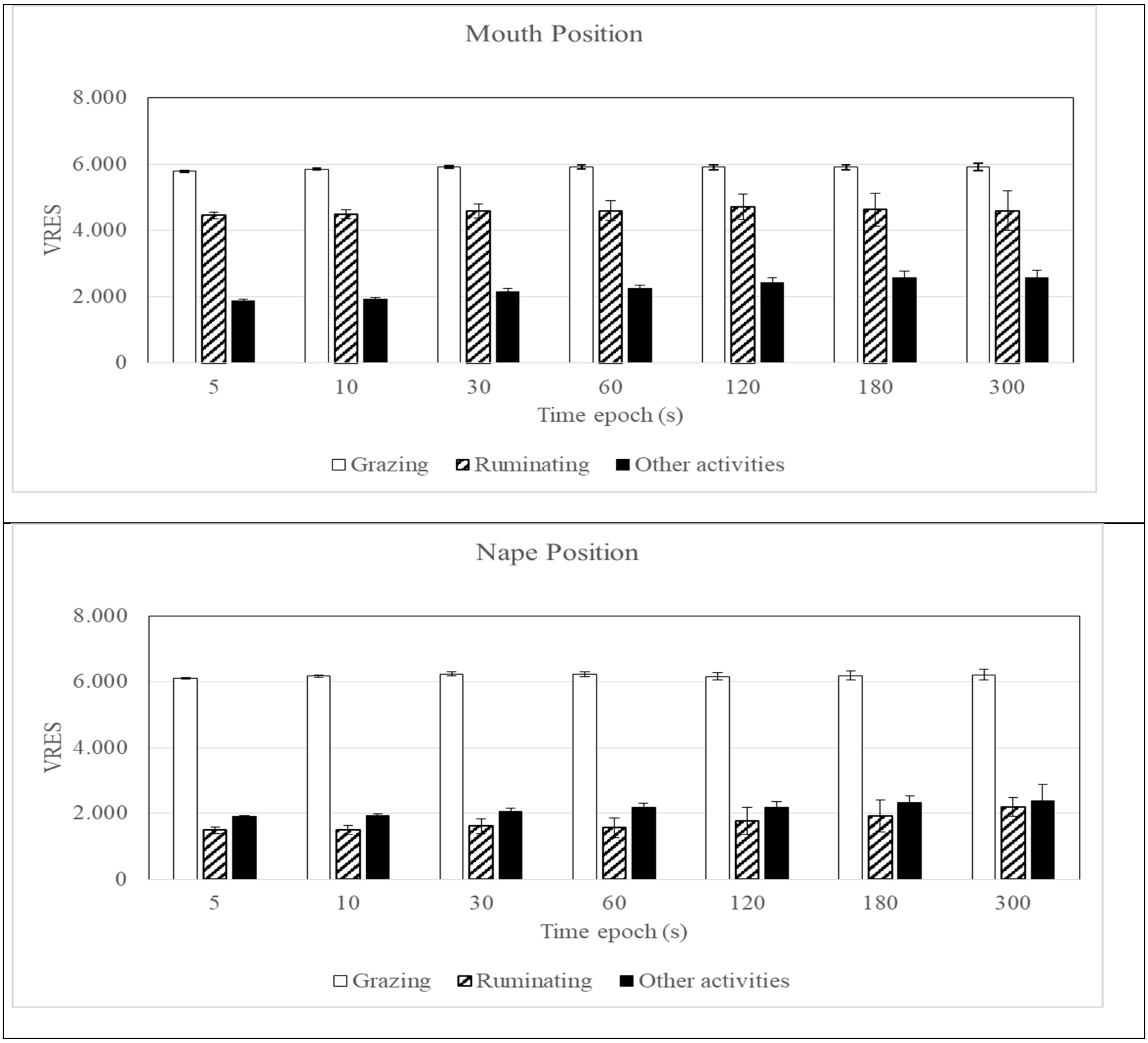
Accuracy = $\frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}}$;

where TP, TN, FP and FN are true positive, true negative, false positive and false negative counts respectively. F-score combines precision and sensitivity into one numerical measure and it was calculated as the harmonic mean of precision and sensitivity. This index reaches the best and the worst score at 1 and 0, respectively (Mitchell, 1997). 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

3.1. Discrimination between behaviour activities

In developing multivariate techniques, the MRES variable was discarded from the analysis because it was not linearly independent from the other variables. In all sensor position and epochs studied, the CDA significantly discriminated between the three behaviours (Hotelling's test P < 0.0001) by extracting two canonical functions (CAN1 and CAN2) for each sensor position and epoch set. The variance explained by CAN1, ranged among epochs between 0.90 and 0.92 in mouth position, 0.94 and 0.99 in nape position and 0.87 and 0.96 in collar position. The variance explained by CAN2 ranged between 0.08 and 0.10 in mouth position, 0.01 and 0.06 in nape position and 0.03 and 0.13 in collar position. In fact, CAN1 was able to significantly separate, for all positions and epochs, the three behaviors unlike CAN2. The variance explained by CAN1 and CAN2 as well as the CC values for each position and epoch are presented in supplementary materials. In mouth and nape positions the variable with the highest CC in CAN1 was VRES (the resultant variance of the three axes), whereas in collar position it was MX (the mean of X axis). The trend of these variables, expressed as a mean of the entire dataset for each epoch in the 3 behaviours studied, for the different positions and time epochs, is reported in Figure 2. In nape and collar positions CAN1 discriminates the grazing activity from that of ruminating, while other activities being intermediate, whereas in mouth position CAN1 discriminates grazing from other activities, being ruminating intermediate, with the exception of highest epochs (180s, 300s), as confirmed by the Mahalanobis' distances (Table 1). The lowest values of error in assignment, after the bootstrap resampling, were observed in collar and mouth position compared to nape position (Figure 3).


Mouth Position
8.000
6.000
4.000
2.000
0
VRES
5
10
30
60
120
180
300
Time epoch (s)
Grazing
Ruminating
Other activities
Nape Position
8.000
6.000
4.000
2.000
0
VRES
5
10
30
60
120
180
300
Time epoch (s)
Grazing
Ruminating
Other activities

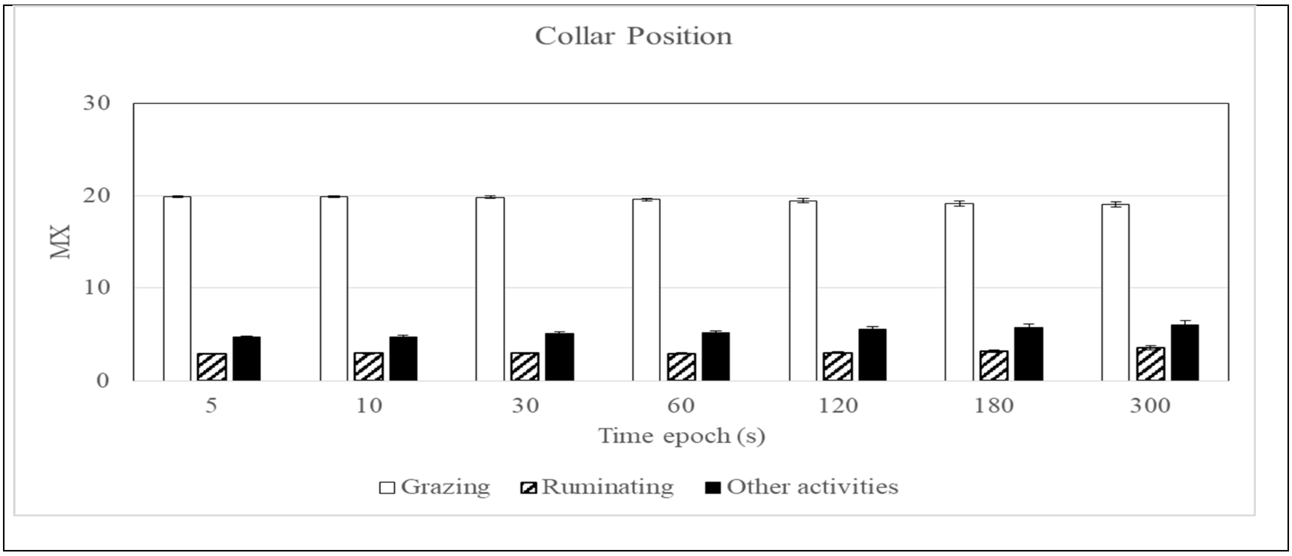


Figure 2. Trend of variables with the greatest contribution to CAN 1 for grazing, ruminating and other activities in different sensor positions and time epochs (means ± SE). VRES= resultant variance of acceleration data of the three axes; MX= Mean of acceleration data for X axis.

Table 1. Mahalanobis distances from main behavioural activities at different sensor positions and time epoch settings.

		Time epoch settings (s)													
Position		**5**		**10**		**30**		**60**		**120**		**180**		**300**	
		RU	OA	RU	OA	RU	OA	RU	OA	RU	OA	RU	OA	RU	OA
Mouth	GR*	5.0	6.6	6.6	8.5	9.6	11.1	11.5	12.1	12.5	12.9	12.4	11.2	14.0	13.8
	RU		1.9		2.3		2.9		3.2		3.7		3.6		4.1
		RU	OA	RU	OA	RU	OA	RU	OA	RU	OA	RU	OA	RU	OA
Nape	GR	4.3	3.3	5.6	4.4	6.8	5.5	7.3	5.7	7.0	6.5	7.1	5.7	6.9	6.6
	RU		0.3		0.4		0.6		0.9		1.1		1.8		1.3
		RU	OA	RU	OA	RU	OA	RU	OA	RU	OA	RU	OA	RU	OA
Collar	GR	6.7	6.2	9.9	8.3	15.9	11.6	20.4	13.8	23.1	14.4	20.9	13.6	26.7	14.4
	RU		0,5		1.0		2.0		3.2		4.9		3.9		9.3

*GR=Grazing; RU=Ruminating; OA= Other activities

Collar and nape positions showed a slight reduction of error in assignment passing from 5s to 300s, whereas mouth position presented a quite constant error values in particular after 30s. The lowest value of error was detected in collar position at 300s epoch (Figure 3).

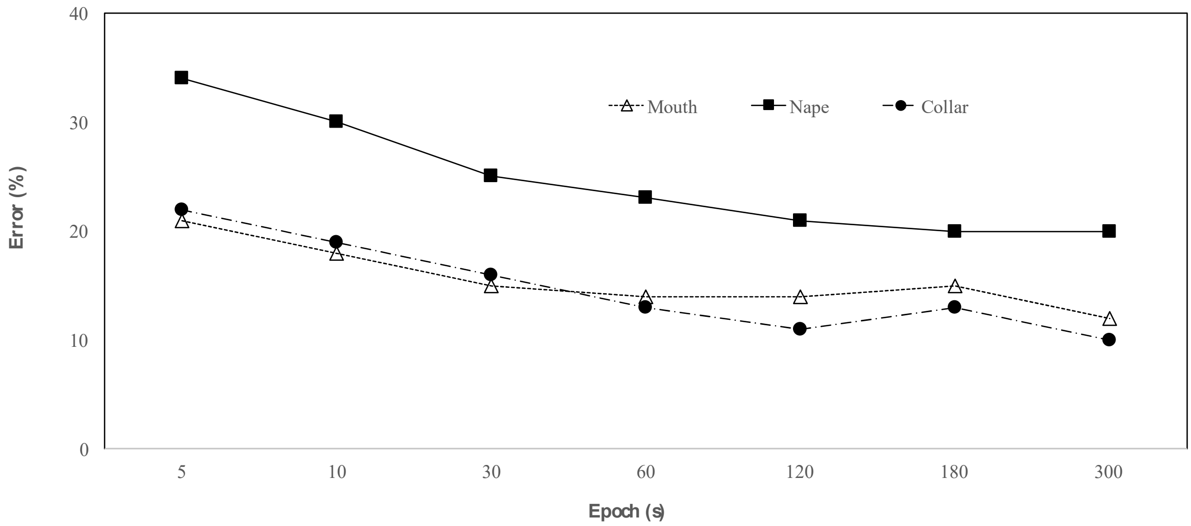


Figure 3. Distribution of errors in assignment of discriminant analysis after bootstrap procedure among sensor positions and epoch settings.

3.2. Performance of the discriminant model analysis

Table 2 reports the performance of DA (Precision, Sensitivity, F-Score, Specificity and Accuracy) for the 3 behaviour studied (grazing, ruminating, other activities) in the different sensor positions and epoch settings. Considering grazing activity, all performance, a part from sensitivity and F-Score, were higher in collar position in quite all the epochs especially when compared to the nape, while the mouth was intermediate. Sensitivity and, consequently, F-Score were higher in mouth position. As regards ruminating, nape sensor position achieved the best performance for precision and specificity. Sensitivity and F-Score showed lower values in ruminating activity for all positions whereas accuracy was rather high and similar in mouth and collar positions.

The best performance of DA model for other activities was detected in mouth and collar position with higher values in mouth at shorter (5s, 10s, 30s, 60s) and in collar at longer epochs (120s, 180s 300s).

Overall accuracy and Coehn's k coefficient are presented in Table 3. On average, the highest values of overall accuracy were found in mouth position for 5s, 10s and 30s epochs (79%, 82% and 85% respectively) similarly to collar position (78%, 81% and 84% respectively), while the lowest were reported in nape (66%, 70% and 75% respectively). Performance turns around for 60s, 120s, 180s and 300s in collar position (87%, 89%, 87% and 90% respectively) that overcame mouth position (86%, 86%, 85% and 88% respectively) the nape position showing the lowest values (77%, 79%, 80% and 80% respectively). The Coehn's k coefficient mirrored the pattern of overall accuracy (Table 3) reaching the highest values in bigger epochs for mouth and collar positioning. The best overall performance of discriminant analysis was obtained using a combination of collar position and 300s time epoch (Table 3).

Table 2. Performance of the discriminant analysis model at different sensor position and time epoch settings (%).

Position		**Mouth**							**Nape**							**Collar**						
Epoch (s)		5	10	30	60	120	180	300	5	10	30	60	120	180	300	5	10	30	60	120	180	300
Grazing	Precision	84.8	88.2	91.4	92.8	92.5	91.9	95.4	80.2	86.3	87.9	88.1	88.1	87.4	87.4	87.7	91.7	93.8	94.8	95.4	94.2	96.9
	Sensitivity	97.9	98.2	97.7	97.5	98.0	97.6	98.6	91.7	91.7	94.4	95.4	96.1	94.6	92.7	94.0	94.8	96.1	97.6	98.0	98.1	96.9
	F-Score	90.9	92.9	94.5	95.1	95.2	94.7	96.9	85.5	88.9	91.0	91.6	92.0	90.8	90.0	90.7	93.3	94.9	96.2	96.7	96.1	96,9
	Specificity	77.1	81.2	85.7	87.2	86.7	85.0	90.8	64.5	72.0	76.0	76.2	75.3	73.7	73.6	79.3	85.3	88.8	90.2	91.4	88.8	93.9
	Accuracy	88.9	91.2	93.0	93.7	93.8	93.0	95.9	81.1	85.0	87.9	88.6	89.0	87.4	86.3	88.3	91.3	93.5	95.0	95.7	94.8	95.9
Ruminating	Precision	52.1	53.3	55.2	55.2	57.1	50.9	55.9	81.3	77.1	77.0	75.8	75.0	81.8	47.1	40.8	47.5	54.0	61.1	67.1	66.7	66.7
	Sensitivity	36.4	41.6	50.3	55.6	58.5	60.0	57.6	14.5	16.1	18.5	20.0	22.4	27.3	24.2	31.8	36.9	47.3	56.3	64.0	59.4	75.0
	F-Score	42.8	46.7	52.6	55.4	57.8	55.1	56.7	24.7	26.7	29.8	31.6	34.5	40.9	32.0	35.8	41.5	50.4	58.6	65.5	62.8	70,6
	Specificity	94.3	94.5	94.9	94.9	95.0	94.7	94.7	98.8	98.6	98.6	98.6	98.6	98.9	96.2	93.6	94.3	95.1	95.9	96.3	96.2	96.2
	Accuracy	85.8	87.6	89.9	90.9	91.3	91.7	90.9	76.7	80.2	82.9	84.7	86.4	88.3	87.4	86.0	87.2	89.9	91.8	93.0	92.0	94.2
Other activities	Precision	76.7	78.6	79.9	79.7	80.6	81.5	80.9	23.4	26.1	39.9	48.2	53.5	56.6	65.1	66.8	64.5	70.5	76.0	80.7	76.6	81.0
	Sensitivity	65.1	67.9	70.8	70.1	68.8	65.5	72.4	46.9	55.7	66.3	69.4	68.5	69.8	70.7	62.5	66.1	69.8	72.6	76.5	72.0	77.1
	F-Score	70.4	72.8	75.1	74.6	74.3	72.7	76.4	31.3	35.6	49.8	56.9	60.0	62.5	67.8	64.6	65.3	70.2	74.2	78.6	74.2	79.0
	Specificity	92.0	92.7	93.1	93.4	93.9	94.3	94.6	77.6	78.7	81.8	84.2	86.5	87.2	89.6	88.7	88.3	90.0	92.3	93.9	93.3	94.3
	Accuracy	84.2	85.7	86.9	87.1	87.1	86.3	89.3	73.4	75.9	79.4	81.7	83.2	83.9	85.6	81.7	82.9	84.9	87.3	89.6	88.3	90.1

Table 3. Overall accuracy and Coehn's k coefficient of the discriminant analysis model at different sensor position and time epoch settings.

Epoch	Mouth		Nape		Collar	
	Accuracy	Coehn's k	Accuracy	Coehn's k	Accuracy	Coehn's k
5s	79 %	0.6	66 %	0.3	78 %	0.6
10s	82 %	0.7	70 %	0.4	81 %	0.6
30s	85 %	0.7	75 %	0.5	84 %	0.7
60s	86 %	0.7	77 %	0.5	87 %	0.7
120s	86 %	0.7	79 %	0.6	89 %	0.8
180s	85 %	0.7	80 %	0.6	87 %	0.7
300s	88 %	0.8	80 %	0.6	90 %	0.8

4. Discussion

4.1. Discrimination between behaviour activities

CDA significantly distinguished the three different behaviours. In particular, CAN1 accounted for most of variation in all positions and epochs, thus clearly separating grazing from ruminating and other activities. This result is confirmed by the Mahalanobis' distances (Table 1) that are greater either between grazing and ruminating (collar and nape position) or between grazing and other activities (mouth position) than between ruminating and other activities, in agreement with findings of Decandia et al., (2018). Jaw movements are surely most frequent in grazing and ruminating than other activities, which includes mainly resting, thus affecting the sensor especially if positioned in mouth.

However, jaw movements from grazing are very different from those of rumination, allowing the DA to distinguish between these two activities. Grazing jaw movements are actually composed by irregular sequences of biting, chew biting, chewing and swallowing while rumination is a quiet and regular cyclic process of regurgitation, chewing and swallowing.

VRES represents the variable with the greatest influence on the variation of CAN1, which discriminate mainly grazing activity from the others two behaviours (ruminating and other activities), when the sensor is placed in the animal's mouth and nape (Figure 2). In those positions the sensor is more solicited by jaw movements (mouth position) and head movements (mouth and nape position) than in collar position, in particular in grazing activity that includes various dynamic movements such as biting, chewing and head shaking while lowering the head. For that reason, in mouth and nape position, VRES, which measures the total amount of variation of the acceleration signal through three dimensions, can differentiate grazing from other behaviours.

Positioning the sensor in the collar it smooths the effect of jaw/head movements; actually, the variable that showed the highest CC for CAN1 is MX (the mean of accelerations in the axis X) that encompasses movements in the backward-forward direction. The sensor behaves like a pendulum as the animal lower the head while grazes and rips the grass with a blow.

Collar and mouth positions showed the lowest errors in assignment (Figure 3) compared to nape position. The low error in assignment in collar position is a comforting result from the point of view of animal welfare being grazing sheep, especially on extensive farms, accustomed to the use of leather collar with the hanging bell. The error in assignment of accelerometer mouth position is in line, even if a little bit higher, with what previously found with the same sensor (Giovanetti et al., 2017a; Decandia et al., 2018). The effect of epoch setting on assignment error showed a slight reduction in collar and nape positions, whereas in mouth position it decreased passing from 5 to 30-60s epochs, and then stabilizing (Figure 3). This result partially confirms what was already observed with the same device by Decandia et al. (2018). In that study the effect of epochs was stronger with best results (lowest assignment error) in 30 and 60s epochs, that can be explained to the difference of the forage species tested. In the present experiment, a chicory-based pasture was used. Chicory is a plant characterised by a rosette growth habit and large, tender leaves usually slowly grazed by sheep with high bite mass (as fresh matter) but low bite rate (Giovanetti et al., 2011). Therefore, the discrimination of the behaviours, in particular grazing, probably needs longer epochs.

4.2. Performance of the discriminant model analysis

Collar position showed the best performance on the discriminant analysis for grazing activity overall, with the only exception being the sensitivity metric that was better in mouth position (Table 2). In the latter position, a very high proportion was correctly identified (true positive) as grazing, while ruminating and other activities being misclassified (false positive). This may be due to the high detection of the jaw movements in mouth position, being more frequent in grazing activity. Precision and sensitivity in mouth and collar positions were similar to what recorded by Fogarthy et al., 2020 in Merino sheep for grazing activity with an epoch of 10s whereas specificity was lower. A slightly higher performance of classification algorithm, using machine learning techniques, was instead reported by Mansbridge et al., (2018) for grazing using accelerometer and gyroscope sensors attached to collars and ear tags on sheep.

Nape sensor position recorded the best performance in terms of precision and specificity for ruminating. Both parameters include at the denominator the false positive (misclassified as ruminating) that for nape position were very few. False negative (ruminating misclassified as grazing or other activities) were conversely high thus affecting sensitivity and, as consequence, F-Score showed very low values in ruminating activity for this position. Since the sensor fails to capture accelerations caused by jaw movements, but not those of the head, the acceleration amplitude during rumination is smoothed and therefore confused by the DA with movements related to other activities. This is actually demonstrated by the very low precision of other activity.

Accuracy in ruminating discrimination was slightly higher in collar than in mouth position in particular in the highest epochs. The discriminant model analysis showed the best performance in mouth and collar positions in other activities classification (Table 2). Mouth position confirmed best performance at shorter epochs (Decandia et al., 2018) whereas collar position at longer ones.

Overall accuracy was higher in collar and mouth than nape position as well as Coehn's k coefficient of the discriminant analysis model (Table 3). The highest overall accuracy of 90 % was obtained for collar data at 300s, similarly to what reported by Mansbridge et al., 2018 with a sensor placed in the same position in sheep using a random forest classification model. In another study (le Roux et al., 2017), a collar tri-axial accelerometer in Merino sheep showed instead lower predictive accuracies. Several studies compared accelerometer-sensor positions in sheep, some of them finding different and often contrasting results of classification models (Barwick et al., 2018a, b; Mansbridge et al., 2018). Barwich et al., (2018a) aiming at discriminating normal and lame gait in sheep with tri-axial accelerometers mounted on collars, front leg, and on an ear-tag, recorded best results with the last sensor position. The same authors (Barwich et al., 2018b) confirmed the highest accuracy from eartag deployed accelerometer also for standing, grazing and walking behaviours classification in sheep. Classification of grazing, ruminating and non-eating, in another study in U.K. with sheep, using collar data, yielded better performances than ear data (Mansbridge et al., 2018). These contrasting results were explainable by the different aim of these studies and the different behavioural activities recorded. In other papers, the authors did not detect big differences of sensor position in classification models results. Walton et al., (2018), evaluating the effects of position in sheep (ear and collar), sampling frequency (8, 16 and 32Hz) and window size (3, 5 and 7s) of accelerometer sensor on the classification of lying, standing and walking, recorded the best performance using combination of either 32 Hz and 7s or 32 Hz and 5s for both ear and collar sensors with negligible differences. The same authors underlined that the differences between ear and collar position could be substantial for other behaviours such as grazing/browsing. Rahman et al., (2018) revealed that different sensor placement in cattle (halter, collar and ear) could achieve good classification accuracy without any important differences. In the current study collar position showed better behavior classification accuracy than mouth and nape position even if the performance of mouth position was only slightly worse. The choice of the position in commercial farms should be mainly based on practical and animal welfare issues, keeping in mind the targeted behavioural activities. Further studies should be aimed at evaluating the accuracy of accelerometer collar position for detecting health problems and for bite counting estimation. As for the latter, accelerometer device, placed at mouth position, has already shown very good performance either in controlled (Giovanetti et al., 2020) or grazing conditions (Giovanetti et al., 2017a).

5. Conclusion

The current study found that collar-attached more than nape-attached and, to a lesser extend mouth-attached accelerometers are able to distinguish among the three behaviours studied. Accuracy varied depending on the epoch setting but was always higher in 300s, that should imply a reduction in data recording and battery consumption.

The results from this study are promising and could be of significant value for a continuous monitoring of behavior in full respect of animal welfare and health. Placing the sensor in the collar, a widely established practice in grazing sheep wearing collar bells, do not actually disturb the animal and it would allow detecting changes in the eating behaviour of sheep, indicative of health or management problems. These results could potentially contribute to the development of an automated continuous monitoring systems that will make real-time feeding and welfare management possible in dairy sheep.

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