Automatic classification system for grazing, ruminating and resting behaviour of dairy sheep using a tri-axial accelerometer.

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ABSTRACT

A device based on a tri-axial accelerometer was used to measure behavioural parameters of dairy sheep at pasture. Short tests were performed in grazing conditions to collect accelerometer data simultaneously with video recordings of sheep behavioural activities (grazing, ruminating and resting). The raw acceleration data was processed to create 12 variables: mean, variance and inverse coefficient of variation (ICV; mean/standard deviation) for the X-, Y- and Z-axis and the resultant at 1-min intervals. A database inclusive of the 12 acceleration variables and the three behavioural activities detected for each minute was then created. Three multivariate statistical techniques were used to discriminate the behavioural activities using the acceleration data: stepwise discriminant analysis (SDA), canonical discriminant analysis (CDA), and discriminant analysis (DA). Based on the acceleration variables selected by SDA, the subsequent CDA significantly discriminated the three behaviours by extracting two canonical functions. The first canonical function (CAN1) discriminated the grazing activity from the resting and ruminating, whereas the second (CAN2) differentiated the grazing from the ruminating behaviour. After bootstrap resampling, the DA correctly assigned 93.0% of minutes to behavioural activities. Stepwise regression analysis was used to estimate the bite frequency (total number of bites/min) using a subset of acceleration data that contained only

minutes in which sheep were grazing. In this case, 15 variables were tested and out of them, only one was selected, the sum of X-axis value per minute (SX), which explained 65 % of the total variation of the bite frequency.

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

INTRODUCTION

Grazing, ruminating and resting are the main daily activities of ruminants and play a key role in regulating their forage intake. Monitoring these three activities is important to take management decisions in grazing systems. According to Hodgson (1982), daily herbage intake of grazing animals is equal to (bites/unit time) × (intake/bite) × (grazing time). The rate of biting (bites/unit time), i.e. the severing of herbage during the act of grazing, together with the bite mass (intake/bite), represents the intake rate (fresh or dry matter /unit of time). The mean rate of biting over 24 h may be calculated from total bites divided by total grazing time (Penning and Rutter, 2004). The total number of bites as well as the behavioural activities of the animals at pasture can be estimated by either direct observation or using automatic recording systems.

The direct and continuous observation of behavioural activities is labour intensive and time consuming (Ungar and Rutter, 2006). Automatic grazing jaw-movement recorders set up around the muzzle of animals based on electric resistance (Penning 1983; Rutter et al. 1997) or a pressure (Nydegger et al., 2011; Zehner et al., 2012; Ruuska et al., 2016) have been used in discriminating between grazing and ruminating in cattle and sheep with good accuracy. Sound recording has been also identified as a good method for analysing the ingestive jaw movements of grazing ruminants (Laca et al., 1992; Delagarde et al., 1999). The method, using an inward-facing microphone, allows to accurately assess bite rate and, more recently, to distinguish among bites, chews and ruminating jaw movement, as well as combined chew-bites (Laca and Wallis De Vries, 2000; Galli et al., 2006; Ungar and Rutter, 2006). Other systems based on electromyography provide estimates of feeding behaviour by positioning electrodes closely attached to the masticatory muscle of the masseter during jaw movement and measuring electrical potential oscillation in dairy cows (Büchel and Sundrum, 2014).

Recently the use of tri-axial accelerometers, sometimes coupled with GPS sensors (Wark et al., 2007), has been implemented to monitor cattle behaviour, discriminating among different activities of cows at pasture such as lying, standing, resting and grazing (Seo et al., 2006 cited by Watanabe et al., 2008), or walking, drinking and hay intake (Scheibe and Gromann, 2006). Moreover, accelerometers attached to animals allow the measurement of animal energy expenditure (Halsey et al., 2008; Miwa et al., 2015), travel speed (Bidder et al., 2012), activity and feeding behaviour (Robert et al., 2009; Moreau et al., 2009; Watanabe et al., 2008). The most common sampling frequencies used in studies with accelerometer based sensors were 10, 16 and 32 Hz, depending on the frequency of the movement being classified. These instruments usually incorporate a microprocessor and a memory to store data until the device is retrieved. However some sensors can incorporate wireless communication technologies, (ZigBee, Bluetooth, Wibree and WiFi), and are commonly used in sensor network based research works (Aqeel-ur-Rehman et al. 2014). Recorded data can be then processed to, for example, select threshold values that distinguish the behavioural activities (Moreau et al., 2009) or develop a quadratic discriminant analysis of transformed variables that automatically classify different behaviours (Watanabe et al., 2008). Other statistical methods such as the classification tree, k-means classifier, multiple-model adaptive estimation approaches, and multilayer perceptron (MLP)-based artificial neural network (ANN) have been also tested (Schwager et al., 2007; Nadimi and Søgaard, 2009; Nadimi et al., 2012).

Despite the growing literature concerning the use of accelerometers in classifying behavioural activities in grazing ruminants, only few references reported the application of this type of sensors to identify and classify jaw movements i.e. bites (Chambers et al., 1981; Umemura, 2013; Oudshoorn and Jørgensen, 2013). The accurate prediction of the number of grazing bites is of great interest to estimate intake in grazing animals but it remains a challenging goal under field conditions. Automatic bite counts was proposed by Chambers et al. (1981) in cattle and sheep to distinguish between the ripping of grass and other jaw movements. This equipment, which combined a micro-switch, an accelerometer and a mercury-switch to detect jaw movements, head movements and head state (up and down) respectively, showed little difference both in cattle and sheep in the agreement between direct observation and bitemeter estimates of the number of grazing bites. Some progress has recently been achieved by Umemura (2013) that found that pedometer values (counts), obtained by attaching the equipment to the neck collar as a pendulum, are well related to the number of visually observed grazing bites in cattle, even though the determination coefficients may vary from 0.79 to 0.90. Finally, Oudshoorn and Jørgensen (2013) used a 3-axis accelerometer to record cow bites and found that the Z-axis had periodic content consistent with the manual bite markings. Their results were encouraging since the bite frequency automatically recorded was not statistically different from the manual count.

The objectives of this study were: to statistically discriminate the feeding behaviour of sheep into three different classes (i.e. grazing, ruminating and resting) using an X-Bee tri-axial accelerometer based sensor and to estimate the bite frequency (number of bites per min of grazing) on the basis of acceleration variables.

MATERIALS AND METHODS

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.

This current study was conducted from the 28th of 2013 to the 6th of February 2014 over 6 weeks. Three non-lactating adult Sarda ewes were used in the study with an age of 2.6±0.6 years (mean±standard deviation) and live weight of 46.0±1.0 kg. Two animals were used as “focal animal” to monitor the feeding behaviour, the third was used as companion animal.

The ewes were kept in a stall and fed ryegrass hay and commercial concentrate in the first three days of each experimental week. Then, for the subsequent three days, they were accustomed to graze from 0900 to 1600h one of the experimental plots previously established with monocultures of the following forage species: alfalfa (*Medicago sativa* L., week 1), Italian ryegrass (*Lolium multiflorum* Lam., week 2, 3), sulla (*Hedysarum coronarium* L., week 4, 5) and chicory (*Cichorium intybus* L., week 6). These forages were chosen because they are widespread in Mediterranean sheep production systems and stimulate a wide range of behavioural responses, which have been already explored in micro-sward studies by our laboratory (Giovanetti et al., 2011). The seventh day of each week (test day), the feeding behaviour of the ewes was monitored when they were allocated from 0900 to 1600h to a 20 x 20 m observation arena, fenced within each experimental plot using sheep electric net.

Accelerometer device and feeding behaviour recording

On each test day, one experimental sheep at a time was fitted with a halter equipped with a tri-axial accelerometer sensor, positioned under the lower jaw of the sheep. This device detects the animal's movements by measuring the accelerations on the X (longitudinal), Y (horizontal) and Z (vertical) axis (Figure 1).

The sensor is inserted in a micro-electromechanical compact system (MEMS) with on-board peripherals. The central part of the system is an 8-bit high performance microcontroller. It also features integrated modules such as programmers connector, piezoelectric film element, wireless XBee that can transmit up to 1.5 km. The power supply of the system is guarantee by a Lithium-Polymer (Li-Po) battery, connected via on-board battery connector. The acceleration sensor used was the ADXL335 (Analog Devices, One Technology Way, P.O. Box 9106, Norwood, MA 02062-9106, USA), a complete tri-axial accelerometer with signal conditioned voltage output. It records both dynamic accelerations, related to changes in the movements of the sheep and static accelerations (-9.8 m s^{-2}), caused by earth's gravity. The microcontroller samples raw acceleration data at a frequency of 62.5 Hz and encodes the data, through an analogue-to-digital converter with a resolution of 8 bits, into levels ranging from 0 to 255. Then, the microcontroller selects the first three peaks of accelerations per second and axis. In motionless circumstances, the microcontroller is programmed to return values equal to zero (static accelerations) for the three axes. Acceleration data were sent by a wireless XBee system to a nearby computer equipped with an antenna. A software package (DAS Client, Electronic System), installed on the computer, activates or deactivates the accelerometer device and manages data acquisition.

The feeding behaviour of sheep were video recorded during accelerometer deployment by fixed camera (Sanyo Xacti VPC-TH1, Sanyo Electric Co., Ltd. OSAKA, Japan). Video and accelerometer recordings were split into 30-45 min sub-periods during the time on the plots in order to re-align the camera or substitute its memory card. During these recording breaks, the halter with the accelerometer was rotated between the two experimental sheep. 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.

Preliminary data processing

A file including the three acceleration values for each axis and one of the three behavioural activities (grazing, ruminating, and resting) per second, based on the recorded videos, was created. 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. Resting activity included all other activities, basically lying down or standing without rumination, and travelling.

The mean (MX, MY, MZ), variance (VX, VY, VZ) and inverse coefficient of variation (ICVX, ICVY, ICVZ) i.e. mean/standard deviation of acceleration data for each axis and per min as well as the resultant mean (MRES), variance (VRES) and ICV (ICVRES) values of the three axis, per min, were then calculated according to Watanabe et al. (2008).

The video-recorded behaviour of the animals was classified, at 1-min intervals, into one of the three prevailing activities in each minute between grazing, ruminating and resting, therefore the final dataset consisted of the three activities combined with the twelve variables concerning acceleration.

A subset of data that contained only minutes in which sheep were grazing was extracted from the final dataset and the number of bites per minute, counted from video recorded files, was added. Three other variables, the sum of the acceleration values per each axis and per min (SX, SY, SZ), were included to the subset that, at the end, contained 15 accelerometer variables.

Statistical analysis

An exploratory analysis of the final database was conducted using a one-way ANOVA model to test the effect of behavioral classes (three levels: grazing, ruminating and resting) on each single accelerometer variable. The Bonferroni correction was adopted to control the multiple testing error rate. Three multivariate statistical techniques were used to discriminate the three behavioural activities: stepwise discriminant analysis (SDA), canonical discriminant analysis (CDA), and discriminant analysis (DA). All statistical analyses were performed by using the SAS software (SAS Institute Inc, 2014).

Twelve variables concerning accelerations (MX, MY, MZ, VX, VY, VZ, ICVX, ICVY, ICVZ, MRES, VRES, ICVRES) and one categorical variable containing the three activities (grazing, ruminating, resting) were used in the analysis. The SDA was exploited to select variables that better discriminated groups. This step was crucial to avoid over-fitting problems when new activities are going to be assigned to one of the three behaviors. Moreover, considering that the battery duration depends on the amount of data transmitted or stored, the selection of a reduced set of variables, able to correctly discriminate groups, could partially solve the battery charge problem.

The ability of selected variables in discriminating groups was tested by using CDA (Mardia et al., 2000). In general, if *k* indicates the number of groups, the CDA derives *k*-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:

$$\mathrm{CAN} = c_1 X_1 + c_2 X_2 + \ldots\ldots.. + c_n X_n$$

where c_i are the canonical coefficients (CC) and X_i are the scores 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. The distance between groups 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 exploited to classify objects into one of the involved groups. In practice, the canonical functions are applied to each object thus producing a discriminant score. An object is assigned to a particular group if its discriminant score is lower than the cutoff value obtained by calculating the weighted mean distance among group centroids (Mardia et al. 2000).

To validate the derived discriminant functions, the complete dataset was randomly divided into training and validation dataset in the proportion of four to one. This partition of the dataset was iterated 5,000 times by using a bootstrap procedure (Efron, 1979). At each run, DA was applied to the training dataset to predict behaviors in the validation dataset and errors in assignment were recorded.

To evaluate the performance of DA for discriminating the three behaviour 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 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 behavior and overall. The K values were judged according to criteria of Landis and Koch (1977).

The subset of data containing only grazing behaviour was analysed by regressing the video recorded rate of biting (number of bites per minute) on the acceleration variables (MX, MY, MZ, VX, VY, VZ, ICVX, ICVY, ICVZ, MRES, VRES, ICVRES, SX, SY, SZ) by using a stepwise model to select the best variables subset to predict the number of bites.

RESULTS

Since the variation of each variable was great, especially for maximum values, data were edited by using as threshold values the mean of each variable plus two standard deviations. After correction, the final dataset contained 675 minutes.

The ANOVA model applied to all variables is displayed in Table 1. Apart from VZ and VRES, for which ruminating and resting were similar, the three activities were significantly different. The highest values were obtained for grazing followed by ruminating and resting.

Discrimination of behaviour activities

SDA applied to the entire dataset selected seven (Table 2) among the twelve original variables. The subsequent CDA significantly discriminated the three behaviours (Hotelling's test $P < 0.0001$) by extracting two canonical functions. The variance explained by CAN1 and CAN2 was 0.68 and 0.32, respectively. Canonical coefficient (CC) values, reported in Table 2, show that both in CAN1 and CAN2, the greatest CCs were for VRES and VZ.

Figure 2 shows that canonical functions can separate the three behavioural activities. CAN1 discriminates the grazing activity from the resting and ruminating ones, whereas CAN2 differentiates the resting from the ruminating behaviour. In particular, the lowest Mahalanobis' distance was obtained between ruminating and resting (183), whereas greater distances were obtained for grazing and ruminating (324) and grazing and resting (311).

After the bootstrap resampling, the DA correctly assigned 93% of minutes to behavioural activities. Errors in assignment, specificity, sensitivity, precision and accuracy of DA for discriminating the sheep behavior activities and K coefficient of agreement between observed and predicted values are displayed in Table 3. The overall accuracy in DA assignment of minutes to the three behaviors was 93%. The precision was 95% for grazing, 94% for resting and 89% for ruminating. The activity with the highest sensitivity (96%), specificity (97%) and accuracy (96%) of classification was grazing. Ruminating and grazing were predicted with the same specificity (97%). About 10% of rumination was misclassified as resting since these two activities are similar for some of the variables considered in the DA (VRES and VZ). Resting activity reported lower specificity (95%) and accuracy values (94%) than grazing and ruminating.

Prediction of rate of biting

Stepwise regression selected only SX and this explained 65 % of the total variation for rate of biting. The intercept was not significantly different from zero ($P = 0.66$) but the slope (0.06) was highly significantly different from zero ($P < 0.001$).

DISCUSSION

Discrimination of behaviour activities

Under the conditions of this experiment, all accelerometer variables had the highest value when the sheep were grazing, the lowest while resting, being the rumination response intermediate (Table 1). Actually when the sheep is grazing, all axes are involved in detecting different dynamic movements with a strong preponderance of vertical axis (Z). Grazing activity is a complex process. The sheep while walking or standing lower and raise its head to search the herbage, gathers and manipulate the herbage with their lips, grips it between its incisors and severe it from the sward (biting) often with a jerk of the head (vertical movement). The herbage severed is then chewed, formed into a bolus and finally swallowed (Penning and Rutter, 2004). Biting and chewing may be carried out simultaneously as "chew-bites" (Laca and Wallis De Vries, 2000). This activity determines horizontal, vertical movements of the head and lateral and vertical movement of the jaw.

In ruminating, movements of the head and jaw are more regular related to regurgitation, chewing and swallowing of merycic boluses. This activity involves lateral and vertical movements of the jaw that are mainly revealed by the Y and Z-axis of the sensor. Resting activity, which includes sheep lying down, standing or travelling in absence of jaw activity, reports the lowest values for almost all variables in all axes with the exception of VZ and VRES values (Table 1) that are similar to ruminating probably because of a lower variability of vertical movements of the head in these two activities.

The SDA selected 7 variables (Table 2) out of the 12 original ones. In particular, all variances (VX, VY, VZ and VRES) one mean (MZ) and two ICV variables (ICVX and ICVZ) were included in the final model.

Watanabe et al. (2008) in a similar experiment involving grazing cows, found that the best discrimination among the three behaviour classes (95.7% of correct assignment) was obtained by retaining 8 variables: MX, MY, MZ, MRES, ICVX, ICVY, ICVZ, ICVRES. The above cited authors suggested that mean variables were effective in detecting body posture (static acceleration) whether the ICV variables detected well both differences in body posture and movements (dynamic acceleration) for each activity.

In the present experiment, means are less important than variances and ICVs in detecting activities probably because accelerations related to the head and jaw movements are more variable in sheep than in cows, particularly when grazing. This result is in agreement with Chambers at al. (1981) who reported, similar wave forms of the accelerometer outputs during grazing in sheep and cows but with higher variability of acceleration and peak values in sheep than cows. The authors ascribed these results in part to the greater inertia of the cow's head movement and in part to the typical cow's head movement that involves some circular movement. In sheep, on the other hand, head movement is essentially backward and forward in the longitudinal axis of the body. Moreover, sheep make greater use of the lips in manipulating herbage that causes a greater ratio of jaw to head movements than cows. Actually cattle are able to open their mouth wider than sheep and to increase the grazed area by extending their tongue thus reaching both an higher herbage mass per bite (bite mass) and an higher herbage intake rate (g DM/min). Parsons et al. (1994) suggested that the main factor affecting intake rate was the handling time, i.e. the time required to take a bite of herbage of a given mass and to manipulate and chew that herbage before swallowing it. The higher intake rate achieved by cattle than sheep is due to a lower proportion of total jaw movements allocated to masticate herbage during grazing. This is probably related to their higher rumen retention time that allows better fiber fermentation in the rumen and requires a lower number of mastication jaw movements per bite of herbage ingested (Van Soest, 1994). It can be stated the sheep have higher handling costs than cows per unit of herbage ingested that causes a greater variability in jaw/head movements and, as a consequence, in accelerations.

Although sheep have probably a different accelerometer pattern than cows while grazing, part of the higher variability of the acceleration detected in this experiment rather than in others focused on cattle (e.g. Watanabe et al., 2008) could be due to the wide range of forage monocultures tested in this experiment. In fact, these forage species are known to give different foraging responses (Giovanetti et al., 2011) and probably affect differently the movements and accelerations associated to their biting and chewing.

If we look to the contribution of the X, Y and Z-axes to the discriminant function, we can observe that the Z-axis (vertical body axis) is always represented with the three categories of variables (mean, variance and ICV). This result can be explained considering that during all monitored behaviours (namely grazing, ruminating and resting) vertical movements are always performed by the animal.

CDA was then exploited to verify if, on the basis of the variables selected by the SDA, minute data came from different behaviour activities. The CAN1 versus CAN2 scatter plot (Figure 2) displayed a clear separation among the three behaviours. In particular, CAN1, which accounted for 68 % of total variability, was able to separate grazing from the other two behaviours. This marked difference is confirmed by the ANOVA results that reported greater values in grazing activity than ruminating and resting. To separate the ruminating from resting, the second canonical function (CAN2), which explained the remaining 32 % of variance, is needed. In both CAN1 and CAN2, the variables VRES and VZ showed the highest absolute CC values (Table 2). This result indicates that the separation of the three behaviours is mainly determined by those variables. This was an expected result because VRES combines the variances of the three axis X, Y and Z and VZ is one of the most important variable in the three activities. Furthermore, the Hotelling's test was highly significant for all the Mahalanobis' distances.

In our experiment, we found a precision of 95% for grazing, 94% for resting and 89% for ruminating (Table 3). This result is slightly lower than what found by Watanabe et al (2008) in cattle who reported 98% of correct assignment in grazing behaviour, followed by resting (92.8%) and ruminating (92.3%) activity.

An important outcome of the present study is the high statistical agreement (0.89), determined with K coefficient, which represents a measure of fortuity (or not) agreement between observed and predicted by the model for each behaviour (Table 3). Among the three behaviours, grazing showed the highest agreement (K = 0.92). Considering all the performances (sensitivity, specificity, precision and accuracy) in the assignment of behavior activities (Table 3), the results of this validation exercise overall suggest that the technology developed in the present study is particularly appropriate to precisely and accurately monitor sheep grazing behavior.

Moreover, despite some limitation, the results of this experiment outperform the goodness of fit of the classification of grazing behaviour reported by other authors in sheep, even when no distinction between rumination and resting was tempted.

For instance, Marais et al., (2014), placing a tri-axis accelerometer device around the neck of the sheep, were able to identify different sheep behaviours with a high accuracy for standing, walking and running (95.2%, 93.7% and 99.5% of correct assignment, respectively) but grazing was misclassified as lying in 35% of cases. McLennan et al. (2015), validating an automatic recording system, was only able to distinguish between active (miscellanea including grazing, walking, standing, ruminating and standing) and inactive behaviours (lying ruminating and lying) in sheep without giving any indication of the specific activity performed by the animal. More recently, Alvarenga et al. (2016), positioning a 3-axis accelerometer under the lower jaw of the sheep, achieved 84.3%, 97.3% and 92.9% for sensitivity, specificity and precision with K of 0.79 in classifying grazing behaviour considering a length epoch of 5 seconds. Although these authors obtained results similar to ours, they reported an overall lower accuracy (81.9% vs. 93.0%) and were unable to measure rumination activity, which is of high nutritional relevance.

Prediction of rate of biting

The stepwise regression, applied to the subset of the final dataset, selected only one variable, the sum of acceleration in the X-axis per minute (SX), thus confirming that the head movement during biting is mainly backward and forward in the longitudinal axis of the body. Our results confirm the difficulty, to count bites using an accelerometer in field condition, in line with the few studies available in the literature, to the best of our knowledge.

The partial agreement with visual observation (65%) obtained in the regression model is probably explainable by different reasons such as: 1) the sensitivity of accelerometers could provide undesirable signals during recording sessions due to head movements not related to grazing activity; 2) the rate of biting is so high in sheep that is sometimes difficult to capture the single bite event, unless video recording is run from very close or under controlled conditions (micro-sward trials); 3) the visual bite count includes also chew-bites that probably produces acceleration signals different from those originated by bites alone.

Finally, we cannot rule out that using raw signal analysis of accelerometer data can provide better prediction of rate of biting or total bite number than using the sum of acceleration values in the X-axis per minute, as found in cows by Andriamandroso et al., (2015) who obtained a mean error of about 5 %.

CONCLUSION

Accelerometers combined with wireless communication technology are useful tools to discriminate grazing, ruminating and resting behaviour activities of grazing sheep. The multivariate statistical approach allowed to reduce the number of variables that are needed to assign acceleration minutes to the appropriate behavior classes with a mean accuracy of 93% and K coefficient of 0.89. Some ruminating activities were misclassified as resting probably because the latter included walking and other non classified activities.

The sum of accelerations in the X-axis per minute provides a good proxy of the number of bites per minute. Better performances could be obtained in the future by processing data with different time epochs and possibly using raw data instead of minute-based statistical parameters.

Other sensors could be added to this device in order to improve the overall classification accuracy and to effectively drive the management of pastoral resources.

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REFERENCES

Alvarenga, F.A.P., Borges, I., Palkovič, L., Rodina, J., Oddy, V.H., Dobos, R.C., 2016. Using a three-axis accelerometer to identify and classify sheep behaviour at pasture. Applied Anim. Beha. Sci., 181, 91–99. DOI: http://dx.doi.org/10.1016/j.applanim.2016.05.026.

Andriamandroso, A.L.H., Lebeau, F., Bindelle, J., 2015. Changes in biting characteristics recorded using the inertial measurement unit of a smartphone reflect differences in sward attributes. In: Guarino M. & Berckmans D., 2015. Proceedings of the 7th European conference on Precision Livestock Farming, Precision Livestock Farming ’15, 15-18 September 2015, Milan, Italy, 283-289.

Aqeel-Ur-Rehman, Abbasi, A.Z., Islam, N., Shaikh, Z.A., 2014. A review of wireless sensors and networks’ applications in agriculture. Comput. Stand. Interfaces 36, 263–270. doi:10.1016/j.csi.2011.03.004

Bidder. O.R., Soresina, M., Shepard, E.L.C., Halsey, L.G., Quintana, F., Gómez-Laich, A., Wilson, R.P., 2012. The need for speed: testing overall dynamic body acceleration for informing animal travel rates in terrestrial dead-reckoning. Zoology 115, 58–64. doi:10.1016/j.zool.2011.09.003

Büchel S., Sundrum A., 2014. Technical note: Evaluation of a new system for measuring feeding behaviour of dairy cows. 2014. Computers and Electronics in Agriculture. Volume 108. Pages 12-16, ISSN 0168-1699.http://dx.doi.org/10.1016/j.compag.2014.06.010.

Chambers A.R.M., Hodgson J., Milne J.A., 1981. The development and use of equipment for the automatic recording of ingestive behaviour in sheep and cattle. Grass Forage Sci., 36, 97-105.

Delagarde, R., Caudal, J.P., Peyraud, J.L., 1999. Development of an automatic bitemeter for grazing cattle. Ann. Zootech. 48, 329–339.

De Maesschalck, R., Jouan-Rimbaud, D., Massart, D.L., 2000. The Mahalanobis Distance, Chemometrics and Intelligent Laboratory Systems, 50, 1–18, 2000. doi:10.1016/S0169-7439(99)00047-7.

Efron, B., 1979. Bootstrap methods: another look at the jackknife. Annals of Statistics 7, 1-26. doi:10.1214/aos/1176344552

Fleiss, J.L., 1981. The measurement of interrater agreement. p. 212-236. In: Statistical Methods for Rates and Proportions. 2nd Edition, John Wiley, NewYork.

Galli, J.R., Cangiano, C.A., Demment, M.W., Laca, E.A., 2006. Acoustic monitoring of chewing and intake of fresh and dry forages in steers. Anim. Feed Sci. Technol. 128, 14–30. doi:10.1016/j.anifeedsci.2005.09.013

Gibb M.J., 1998. Animal grazing/intake terminology and definitions. In Proc. Workshop Concerned Action. AIR3–CT93–0947h. Occasional Publ. No. 3. Teagasc, Dublin, Ireland.

Giovanetti, V., Decandia, M., Acciaro, M., Cabiddu, A., Sitzia, M., Picconi, S., Molle, G., 2011. A short-term test to assess sheep propensity towards Mediterranean forages offered as micro-swards. Proc. of the 8th International Symposium on the Nutrition of Herbivores. Advances in Animal Biosciences, Vol 2, Part 2. Pp 314.

Halsey L.G., Shepard E.L.C., Hulston C.J., Venables M.C., White C.R., Jeukendrupb A.E., Wilson R.P. 2008. Acceleration versus heart rate for estimating energy expenditure and speed during locomotion in animals: Tests with an easy model species, Homo sapiens. Zoology 111: 231–241. doi:10.1016/j.zool.2007.07.011.

Hodgson, J. 1982. Influence of sward characteristics on diet selection and herbage by the grazing animal. p. 153-166. In J.B. Hacker (ed.) Nutritional limits to animal production from pastures. CAB, Slough, UK.

Laca, E.A., Ungar, E.D., Seligman, N.G., Ramey, M.R., Demment, M.W., 1992. An integrated methodology for studying short-term grazing behaviour of cattle. Grass Forage Sci. 47, 81–90. doi:10.1111/j.1365-2494.1992.tb02250.x.

Laca, E.A., Wallis De Vries, M.F., 2000. Acoustic measurement of intake and grazing behaviour of cattle. Grass Forage Sci. 55, 97–104. doi:10.1046/j.1365-2494.2000.00203.x.

Landis, J., Koch, G., 1977. The measurement of observer agreement for categorical data. Biometrics 33:159–74.

Marais, J., Le Roux, S.P., Wolhuter, R., Niesler, T., 2014. Automatic classification of sheep behaviour using 3-axis accelerometer data. In Eds M. Puttkammer and R. Eiselen Proceedings of the 2014 PRASA, RobMech and AfLaT International Joint Symposium 27-28 November 2014, Cape Town, RSA pp. 97-102.

Mardia, K.V., Bookstein, F.L., Moreton, I.J., 2000. Statistical assessment of bilateral symmetry of shapes. Biometrika 87, 285–300. doi:10.1093/biomet/87.2.285

McLennan, K.M., Skillings, E.A., Rebelo, C.J.B., Corke, M.J., Moreira, M.A.P., Morton, A. J., Constantino-Casas, F., 2015. Technical note: Validation of an automatic recording system to assess behavioural activity level in sheep (Ovis aries). Small Rumin. Res. 127, 92–96. doi:10.1016/j.smallrumres.2015.04.002.

Miwa M, Oishi K, Nakagawa Y, Maeno H, Anzai H, Kumagai H, Okano, K., Tobioka, H., Hirooka, H., 2015. Application of Overall Dynamic Body Acceleration as a Proxy for Estimating the Energy Expenditure of Grazing Farm Animals: Relationship with Heart Rate. PLoS ONE 10 (6): e0128042. doi:10.1371/journal.pone.0128042

Moreau, M., Siebert, S., Buerkert, A., Schlecht, E., 2009. Use of a tri-axial accelerometer for automated recording and classification of goats’ grazing behaviour. Appl. Anim. Behav. Sci. 119, 158–170. doi:10.1016/j.applanim.2009.04.008

Nadimi, E.S., Søggard, H.T., 2009. Observer Kalman filter identification and multiplemodel adaptive estimation technique for classifying animal behaviour using wireless sensor networks. Comput. Electron. Agric. 68, 9–17. doi:10.1016/j.compag.2009.03.006.

Nadimi E.S., Jørgensen, R.N., Blanes-Vidal, V., Christensen, S., 2012. Monitoring and classifying animal behaviour using ZigBee-based mobile ad hoc wireless sensor networks and artificial neural networks. Comput. Electron. Agric. 82, 44–54. doi:10.1016/j.compag.2011.12.008

Nydegger, F., Gygax, L., Egli, W., 2011. Mesure automatique des mouvements de rumination par capteur de pression. Recherche Agronomique Suisse, 2, 60-65.

Oudshoorn F.W., Jørgensen O., 2013. Registration of cow bites based on three-axis accelerometer data. In: Berckmans D. Proceedings of the 6th European Conference on Precision Livestock Farming, Precision Livestock Farming ’13, 10-12 September 2013, Leuven, Belgium, 771-777.

Parsons, A.J., Thornley, J.H.M., Newman, J., Penning, P.D., 1994. A Mechanistic Model of Some Physical Determinants of Intake Rate and Diet Selection in a Two-Species Temperate Grassland Sward. Funct. Ecol. 8, 187–204. doi:10.2307/2389902

Penning, P.D., 1983. A technique to record automatically some aspects of grazing and ruminating behaviour in sheep. Grass and Forage Science 38, 89–96. doi:10.1111/j.1365-2494.1983.tb01626.x

Penning P.D., Rutter, S.M., 2004. Ingestive behaviour. In: Penning, P. D. Herbage intake handbook. 2. ed. The British Grassland Society, p. 151-176, 2004.

Robert, B., Whitea, B.J., Renterb, D.G., Larsona, R.L. 2009. Evaluation of three-dimensional accelerometers to monitor and classify behaviour patterns in cattle. Comput. Electron. Agric. 67, 80–84. doi:10.1016/j.compag.2009.03.002.

Rutter, S.M., Champion, R.A., Penning, P.D., 1997. An automatic system to record foraging behaviour in free-ranging ruminants. Appl. Anim. Behav. Sci. 54, 185–195, http://dx.doi.org/10.1016/S0168-1591(96)01191-4.

Ruuska, S., Kajava, S., Mughal, M., Zehner, N., Mononena, J., 2016. Validation of a pressure sensor-based system for measuring eating, rumination and drinking behaviour of dairy cattle. Appl. Anim. Behav. Sci. 174, 19–23. doi:10.1016/j.applanim.2015.11.005

SAS Institute Inc, 2014. SAS Institute Inc., SAS Institute Inc. Market Line Company Profile.

Scheibe, K. M., Gromann, C. (2006). Application testing of a new three-dimensional acceleration measuring system with wireless data transfer (WAS) for behaviour analysis. Behav. Res. Methods 38, 427–433. doi:10.3758/BF03192796.

Schwager, M., Anderson, M.D., Butler, Z., Rus, D., 2007. Robust classification of animal tracking data. Computers and Electronics in Agriculture, 56 (1), 46–59. doi:10.1016/j.compag.2007.01.002.

Umemura, K., 2013. Monitoring grazing bites and walking activity with pedometers. Journal of Dairy Science 96, 1090-1093. doi:10.3168/jds.2012-5872.

Ungar, E.D., Rutter, S.M., 2006. Classifying cattle jaw movements: comparing IGER behaviour recorder and acoustic techniques. Appl. Anim. Behav. Sci. 98, 11–27. doi:10.1016/j.applanim.2005.08.011.

Van Soest, P.J., 1994. Nutritional Ecology of the Ruminant. Cornell University, USA. 476 pp.

Wark, T., Corke, P., Sikka, P., Klingbeil, L., Ying, G., Crossman, C., Valencia, P., Swain, D., Bishop-Hurley, G., 2007. Transforming agriculture through pervasive wireless sensor networks. IEEE Pervasive Comput. 6, 50–57. doi:10.1109/MPRV.2007.47.

Watanabe, N., Sakanoue, S., Kawamura, K., Kozakai, T., 2008. Development of an automatic classification system for eating, ruminating and resting behaviour of cattle using an accelerometer. Jap. Grassland Sci., 54, 231–237. doi:10.1111/j.1744-697X.2008.00126.x.

Zehner, N., Niederhauser, J.J., Nydegger, F., Grothmann, A., Keller, M., Hoch, M., Haeussermann, A., Schick, M., 2012. Validation of a new health monitoring system (RumiWatch) for combined automatic measurement of rumination, feed intake, water intake and locomotion in dairy cows. In: Proceedings of International Conference of Agricultural Engineering CIGR-AgEng2012, July 8–12, 2012, Valencia, Spain.

Figure 1. Halter equipped with a tri-axial accelerometer sensor.

Figure 2. Plot of canonical variables (CAN 1, CAN 2) generated from discriminant analysis.

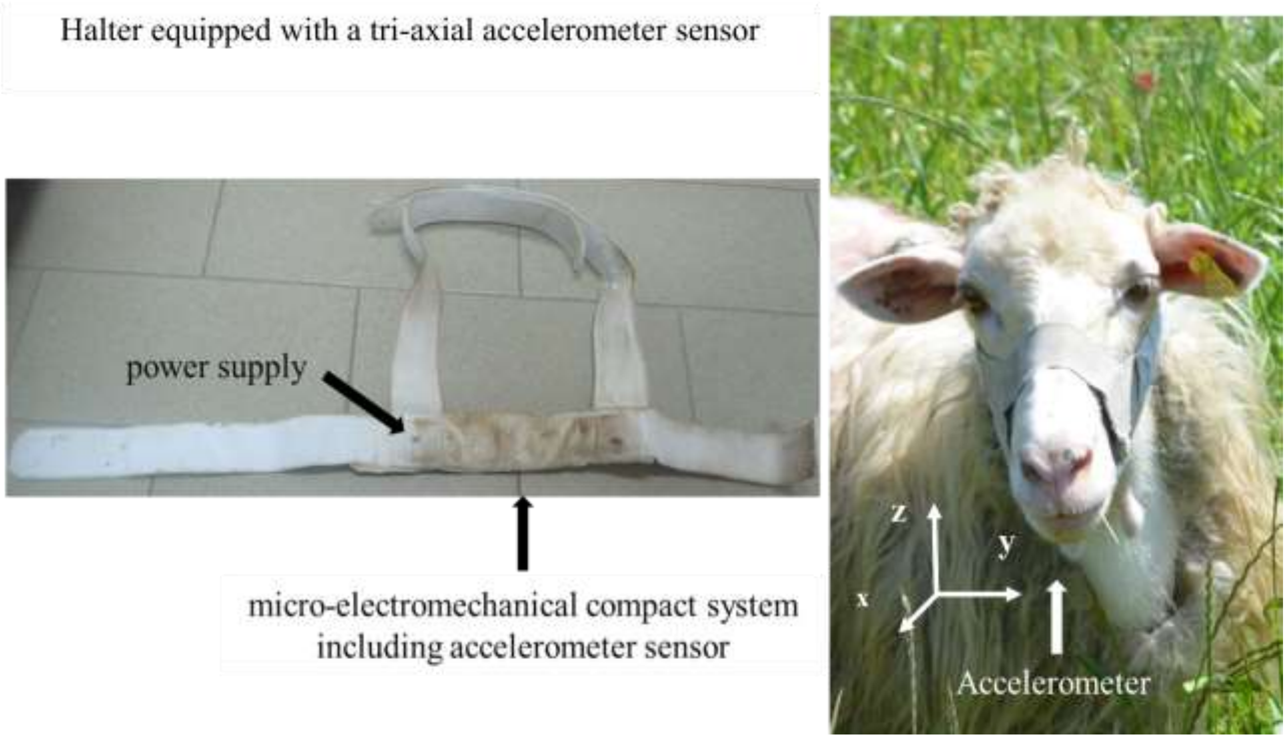

Figure 1. Halter equipped with a tri axial accelerometer sensor.

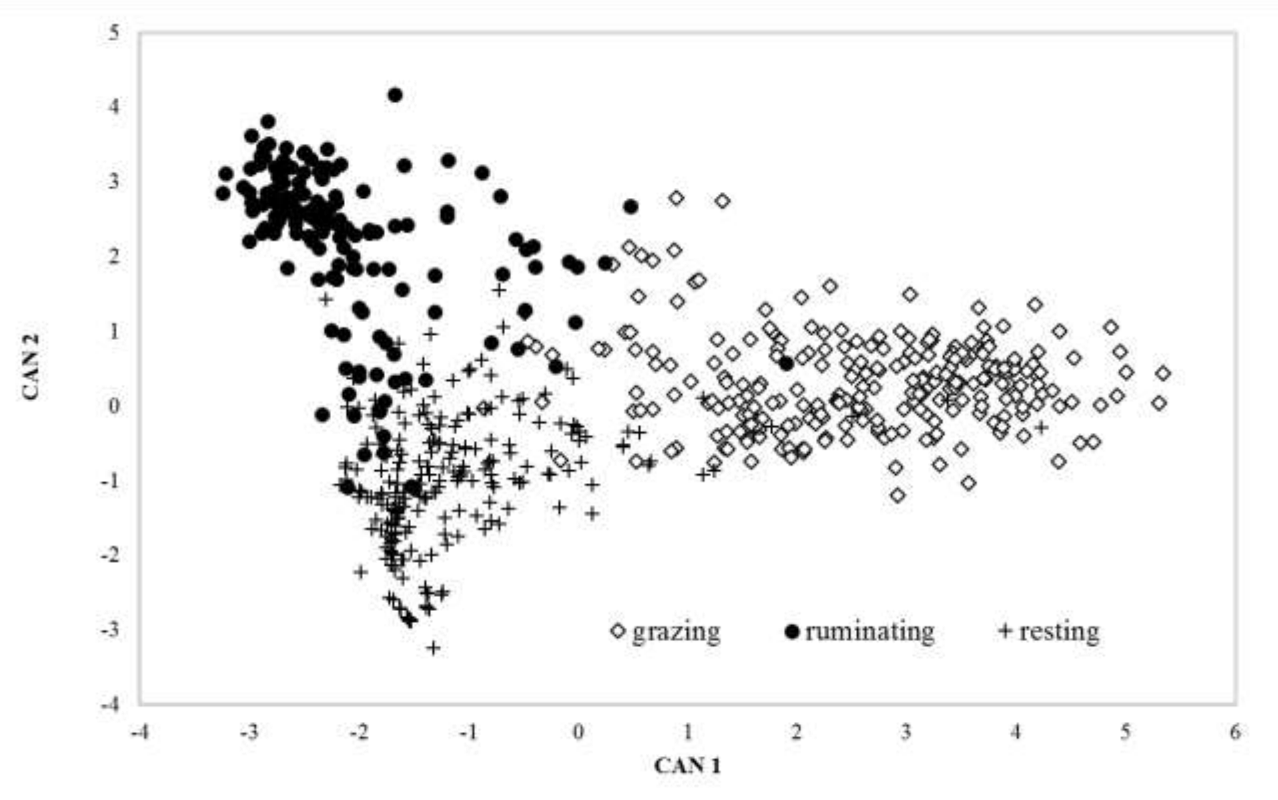

Figure 2. Plot of canonical variables (CAN 1, CAN 2) generated from discriminant analysis.

Table 1. The effect of the behavioural activity classes 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 and Z-axis and the resultant.

	Grazing	Ruminating	Resting	P<
Minutes	247	149	279	
MX	3.14 ± 0.06^{a}	1.5 ± 0.07^{b}	0.54 ± 0.05^{c}	0.0001
MY	4.40 ± 0.07^{a}	2.74 ± 0.09^{b}	0.78 ± 0.07^{c}	0.0001
MZ	6.95 ± 0.11^{a}	1.41 ± 0.14^{b}	0.88 ± 0.10^{c}	0.0001
MRES	4.83 ± 0.07^{a}	1.90 ± 0.09^{b}	0.73 ± 0.07^{c}	0.0001
VX	29.12 ± 0.65^{a}	9.12 ± 0.84^{b}	5.40 ± 0.61^{c}	0.0001
VY	34.33 ± 0.80^{a}	17.44 ± 1.04^{b}	6.69 ± 0.76^{c}	0.0001
VZ	113.25 ± 2.93^{a}	6.34 ± 3.77^{b}	14.57 ± 2.75^{b}	0.0001
VRES	62.03 ± 1.28^{a}	11.42 ± 1.65^{b}	8.96 ± 1.21^{b}	0.0001
ICVX	0.58 ± 0.01^{a}	0.54 ± 0.01^{b}	0.20 ± 0.01^{c}	0.0001
ICVY	0.76 ± 0.01^{a}	0.67 ± 0.01^{b}	0.26 ± 0.01^{c}	0.0001
ICVZ	0.68 ± 0.01^{a}	0.57 ± 0.01^{b}	0.22 ± 0.01^{c}	0.0001
ICVRES	0.63 ± 0.01^{a}	0.57 ± 0.01^{b}	0.22 ± 0.01^{c}	0.0001

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

Table 2. Standardized canonical coefficients.

Variable	Can1	Can2
MZ	4.60	-3.084
VX	2.74	-1.72
VY	3.15	-1.51
VZ	12.80	-6.50
VRES	-19.07	10.53
ICVX	-0.56	1.00
ICVZ	-0.28	1.69

Table 3. Distribution of the total error and performance in the assignment of behavior activities, predicted on the basis of accelerometer data.

Observed behaviour	Predicted behaviour			
	Grazing	Ruminating	Resting	Total
Grazing	234	8	6	247
Ruminating	1	133	15	149
Resting	9	9	261	279
Total	244	149	282	675
Sensitivity (%)	96	89	93	
Specificity (%)	97	97	95	
Precision (%)	95	89	94	
Accuracy (%)	96	95	94	93[#]
k	0.92	0.86	0.89	0.89[$]

[#] Overall accuracy of the discriminant analysis

[$]Kappa coefficient used as overall coefficient of agreement ($P < 0.001$).