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Use of a tri-axial accelerometer for automated recording and classification of goats' grazing behaviour

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ABSTRACT

The suitability of an inexpensive tri-axial accelerometer for the automated recording of goats' activities at pasture was tested on a slightly undulating pasture in Central Germany (52 h of registry) and on a rugged mountainous pasture in northern Oman (70 h of registry). The logger was either mounted onto a chest belt, a dog harness or a neck collar. The device registered the animals' acceleration and changes in head inclination every second (Germany) or every two seconds (Oman). To calibrate and validate the logger's registries, an observer simultaneously recorded the goats' activities, distinguishing between walking, resting and eating; the latter was further subdivided into grazing (head-down) and browsing (head-up). Merged with the observation data, the accelerometer recordings were imported into a specially designed computer programme that calculated moving averages for the transformed accelerometer data and selected threshold values to distinguish resting from eating and eating from walking. Calibration functions established from data sets of a first goat were validated with data from a second goat fitted with the same harness type.

The true recognition of activities detected by the accelerometer and the corresponding programme ranged from 87% to 93% for eating, 68% to 90% for resting and 20% to 92% for walking. It was affected, for resting and walking, by the type of mounting system used for logger fixation (fixed effect; $P < 0.001$) and, for resting and eating, by the number of observations (covariable; $P < 0.01$). Using a dog harness, the programme correctly recognized head-up and head-down positions in 75–82% and in 61–71% of the observed cases, respectively. With solid data sets for the calibration, a reliable automated classification of goats' activities is possible across different individuals and across husbandry systems, provided that the same harness type is used.

1. Introduction

Studies of livestock behaviour can serve three purposes: firstly, activity determination may enable improved management to enhance animal performance such as reproduction and lactation (Roelofs et al., 2005). Secondly, the activity of animals may serve as a health indicator (O'Callaghan et al., 2003), and thirdly, the study of specific activities such as grazing behaviour may improve the understanding of animals' utilisation of the vegetation on offer (Lockyer and Champion, 2001). The development of increasingly powerful electronic instruments with higher sensitivity and larger data storage capacity opens up new prospects for studying animal activity. Such devices facilitate behaviour studies under conditions where manual observation is difficult, as for example during night grazing (Langbein et al., 1996; Scheibe et al., 1998), in mountain environments (Schlecht et al., 2009) or at very

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remote locations (Van Oort et al., 2004). Thereby the precision with which accelerometers allow to distinguish between activities is remarkable: Foerster et al. (1999) arrived at identifying nine different human activities by using four accelerometers simultaneously; Watanabe et al. (2005) distinguished seven activities of a cat using a uni-axial accelerometer, and Cornou and Lundbye-Christensen (2007) used a tri-axial accelerometer to classify five different activities of sows. The activity classifications are based upon the two variables recorded by an accelerometer: (i) the dynamic acceleration provoked by changes in velocity, shock and vibration and (ii) the static acceleration caused by earth gravity. An accelerometer registering numerical data of these two variables thus reflects an animal's level of activity (Müller and Schrader, 2003) and, by measuring inclination (Hanson et al., 2001), also changes in its posture.

Classification of different activities and postures of an animal requires an analysis system that decodes these data. Some studies interpreted the accelerometer raw data by visually comparing it to videotaped activities (Yoda et al., 2001; Okuyama et al., 2004). This approach, however, is subjective, time-consuming and requires good visibility of the animal. Other studies proposed to classify the activities based on mathematical transformation of the raw data (Watanabe et al., 2005; Cornou and Lundbye-Christensen, 2007). However, these approaches are complex and imply an important manual workload, which limits their wide-spread application. Bussmann et al. (1998) proposed to overcome such difficulties by using an 'Activity Monitor' able to integrate the information of four accelerometers for automated analysis of human activities, and Burchfield and Venkatesan (2007) showed that the average acceleration provided by an accelerometer can serve as a calibration for the detection of abnormal human movements.

These examples suggest that it is possible to conceive, on the basis of tri-axial accelerometer data, an automated, simple and broadly valid behaviour analysis system for goats' activities at pasture, which was the objective of the present study. Hereby two features were of specific interest for the automated detection of activities: firstly, the momentum which varies according to the pace of locomotion (Müller and Schrader, 2003); secondly, the posture of the animal which in general makes it possible to measure binary activities like standing/lying (Champion et al., 1997) or head-up/head-down (Scheibe et al., 1998). The spatial orientation of an animal's activity is another important criterion that can be monitored with devices on the ground (Langbein et al., 1996; Fehmi and Laca, 2001) or by satellite telemetry (Rutter et al., 1997). The accelerometer used in our study was therefore combined with a GPS tracking collar to test the device's potential use for spatio-temporal analysis of behaviour reflecting animal–environment interactions.

2. Methods

2.1. Sites and animals

The study was performed in two consecutive parts, of which the first one was conducted in Central Germany between June and August 2007 with two Thüringer Waldziege × Toggenburg crossbred goats of about 65 kg (goat G1) and 50 kg (goat G2) live weight. Together with 24 other goats they continuously (24 h d^{-1}) stayed on undulating fenced pastures of 1–2 ha in size. The second part of the study was conducted on the Al Jabal al Akhdar Plateau in the Northern Hajar Mountains, Oman, between September and October 2007. Here a typical Jabal Akhdar breed goat of about 40 kg live weight (goat O) was provided by a local farmer whereby this animal was herded together with about 70 other goats on communal mountain pastures (Brinkmann et al., submitted for publication; Schlecht et al., 2009) from 7 a.m. to 5 p.m. daily.

2.2. Accelerometer

Due to their small size (58 mm × 33 mm × 23 mm), lightweight (18 g including a long-duration 3 V Li battery) and affordable price (76€ for data logger plus one optical USB data transfer device and download software), two HOBO® Pendant G tri-axial acceleration data loggers (Onset Computer Corporation, Pocasset, MA, USA; http://www.onsetcomp.com/products/data-loggers/) were used for recording of behavioural data. The device operates from −20 to 70 °C and simultaneously records acceleration and inclination through measurement of an analogue signal in each of its three axes (*X*, *Y* and *Z*; Fig. 1a–c). These signals are converted to gravity units ranging from −3 to +3 g (1 g = 9.8 m s^{-2}). The logger's memory of 64 kB permits to record 21,800 three-dimensional data points at user-determined intervals of 1 s to 18 h. On readout, raw data are displayed graphically and can be saved in ASCII format for further processing.

Three types of mounting systems (weighing 242–264 g) for fixing the accelerometer on the goat were tested, whereby the logger was slipped into a small pocket: mounted on top of a broad belt (B) around the goat's chest; mounted on top of a dog harness (H) fixed around the goat's chest; and attached to a neck collar (C). For each mounting system, two adhesive strips of neoprene® were fixed on both sides of the goat's spine to assure an unchanged logger position relative to the back (B), withers (H), or neck (C) as shown in Fig. 1d. During the experiment, the bold end of the logger always pointed towards the animal's head and the tuck ridge pointed to the top. Thus the instrument's *X*-axis corresponded to the vertical dimension, the *Y*-axis corresponded to one horizontal dimension, measuring the acceleration sidewise to the left and right, and the *Z*-axis corresponded to the second horizontal dimension measuring the acceleration forwards and backwards. The values registered when the goat stood still were $X = 0$ g, $Y = 0$ g and $Z = -1$ g.

2.3. GPS tracking collar

The GPS tracking collar (Vectronic Aerospace, Berlin, Germany) consisted of a 12-channel receiver powered by two Li batteries of 3–3.6 V, 10 Ah. The components were placed in a sturdy casing and mounted on a polyester harness adjustable to the animal's neck. Gross mass of the collar was 610 g. Information stored by the GPS were: date,

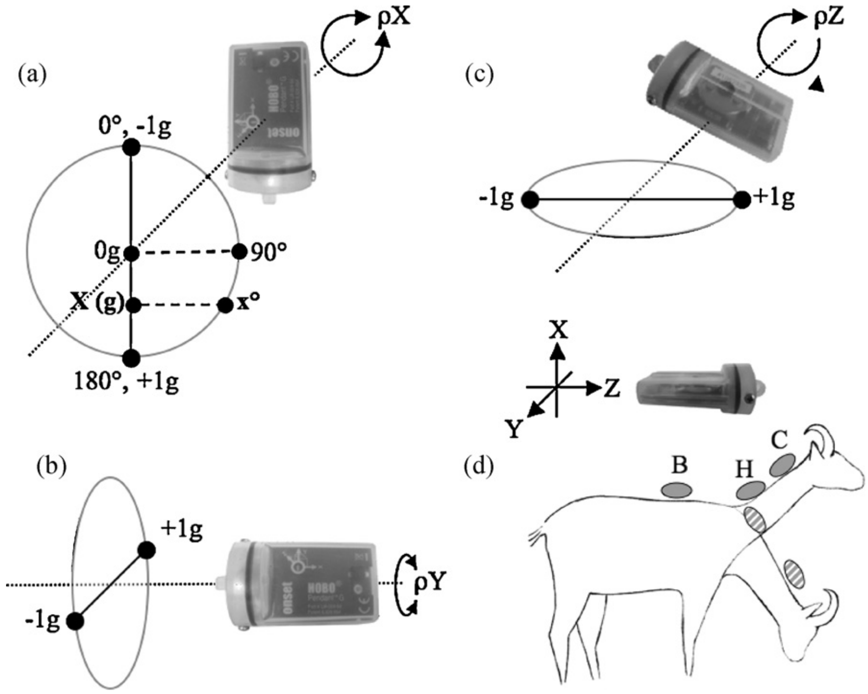

Fig. 1. In drawings a, b and c, the Hobo® Pendant G tri-axial accelerometer is placed such that it measures 0° (−1 g) change for each of the three axes *X*, *Y*, *Z*. The gravitational acceleration values vary according to $x = \cos(180 - x)$ if the logger effectuates a rotation (ρ) on a specific axis, thereby the *X*-, *Y*- and *Z*-axes have a defined position with regard to the logger housing. The logger's position relative to the animal's body must be maintained constant during a series of data collection, regardless of whether it is fixed on a chest belt (B), dog harness (H) or neck collar (C) as shown in schema d for head-up and for head-down position (faded).

time, latitude, longitude (UTM, WGS84 format), altitude, 2D/3D navigation, position dilution of precision (PDOP), number and ID of satellites used for each position calculation, carrier-to-noise ratio and battery voltage. The device had a total storage capacity of 65,536 non-differential GPS positions. Although able to track up to six satellites, the GPS was set to calculate position fixes from the best 3 or 4 satellites (2D/3D mode). According to the manufacturer, the device's mean horizontal deviation from the true position is ±2.5 m.

2.4. Experimental setup

Prior to the experiments, we verified that the two accelerometers produced congruent recordings when submitted simultaneously to the same movements. In Germany, the tests were carried out with goats G1 and G2 that were equipped with an accelerometer each. Both goats were observed simultaneously for 5 experimental periods of 4 h; additionally goat G1 was equipped with an accelerometer for three further periods of 4 h (Table 1). The interval of recording was set at 1 s for all measurements. In Oman, a dog harness holding the accelerometer was fitted to goat O during 7 experimental periods of 10 h each, with the recording interval set to 2 s. Here, the accelerometer was combined with the GPS tracking collar whereby the logging interval of the latter was set to 10 s.

While equipped with the accelerometer, the goats' activities were manually observed every 10 s (sequential approach; Altmann, 1974), thereby distinguishing the activities 'resting' (either standing or lying, with or without rumination), 'eating', and 'walking'; any activity not corresponding to these categories was classified as 'other'. In Oman, the position of the head (head-up or head-down) was also noted to distinguish grazing from browsing, which did not play a role on the herbaceous German pasture. All manual observations were interpolated *ex post* to the 1 s and 2 s recording intervals of the accelerometers. Periods of walking or resting that were interrupted by a single observation of eating were considered to continue if overall they lasted longer than one minute; if not, the goat was considered to be eating during the interval of interpolation.

2.5. Processing of accelerometer data

In order to determine the accelerometer's response to the distinguished activities, the graphically displayed raw data from the HOBO Pendant G were initially compared to the goats' activities as recorded by video taping during sequences of 10–80 min. For each of the three axes of the HOBO logger, a dynamic acceleration induces varying amplitudes of the gravity measurement cell: very weak during resting, average during eating, and large during walking (Fig. 2). To classify the three activities, the information on amplitude was therefore isolated for each axis. While eating, the head-up and head-down movements induce a phase shift along the vertical axis, which with our logger placement was recorded by the *X*-axis.

The accelerometer raw data, consisting of the date, the time and the related impulse in the *X*, *Y* and *Z* dimensions

Table 1
List of single experiments conducted to test a three-axial accelerometer for monitoring goat behaviour in Germany and Oman in 2007.

Data set[a]	Date	Duration (h)	Logging interval (s)	Used to test effect of				
				Mounting system	Individual	Logging interval	Husbandry system	Head position
Germany								
1_G1_B	01.06	4	1		×	×		
1_G2_B	01.06	4	1		×			
2_G1_B	03.06	4	1		×	×		
2_G2_B	03.06	4	1		×			
3_G1_B	04.06	4	1			×		
3_G2_H	04.06	4	1		×		×	
4_G1_B	05.06	4	1			×		
4_G2_H	05.06	4	1		×		×	
5_G1_B	06.06	4	1			×		
5_G2_H	06.06	4	1		×		×	
7_G1_C	27.07	4	1	×				
7_G1_H	27.07	4	1	×	×		×	
8_G1_B	31.07	4	1	×				
8_G1_C	31.07	4	1	×				
9_G1_B	21.08	4	1	×				
9_G1_H	21.08	4	1	×	×		×	
Oman								
1_O_H	05.10	10	2				×	×
2_O_H	06.10	10	2				×	×
3_O_H	07.10	10	2				×	×
4_O_H	08.10	10	2				×	×
5_O_H	09.10	10	2				×	×
6_O_H	15.10	10	2				×	×
7_O_H	16.10	10	2				×	×

[a] The number stands for the day (first, second, etc.), the first letter for the name of the animal and the second letter is indicating the type of logger mounting system used, namely chest belt (B), dog harness (H) and neck collar (C).

was merged with the corresponding manual observation of activities classified as 'resting', 'eating' or 'walking' and on the head position during eating, classified as 'grazing' (head-down) or 'browsing' (head-up). The resulting file with its seven columns (training data set) was imported into the custom-designed, C++-based software tool 'Animstat' (to be obtained from the authors upon request), which consists of a training (calibration) module and an application (analysis) module (Fig. 6). In the training module, the observed animal activities are used to compute the parameters that are required thereafter in the application module to assign an activity to each (unobserved) accelerometer record. The mathematical procedures implemented in this tool are explained in the appendix. In brief, the head position is derived from the inclination (cosinus) of the *X*-axis, while the activities resting, eating, and walking are assigned according to threshold values separating resting from eating and eating from walking, respectively. Thresholds are calculated and tested for each axis separately; the final classification is based on the majority of classification decisions. If, for example, according to the *X*- and *Y*-axis signals a record is classified as 'eating' and according to the *Z*-axis it classifies as 'walking', the attribute is 'eating'. If the classification differs for all three axes, the axis showing the highest probability according to the programme's routine is used to classify the record.

2.6. Calibration and validation of automated classification

To calibrate and validate the combined use of the accelerometer for data collection and of the 'Animstat' software for automated data classification, a series of tests was run (Table 1):

(i) To determine whether the position of the accelerometer on the animal affects the activity classification, the recordings of two accelerometers attached to two different mounting systems on the same goat were compared.
(ii) To test whether the threshold values for activity classification generated from the calibration data set of one goat can be used to determine the activities of a second goat, the data sets obtained for goat G1, wearing either the chest belt or the dog harness, were used as calibration data set for the classification of accelerometer data of goat G2 wearing the respective type of mounting system, and *vice versa*.
(iii) To determine whether the accuracy of activity classification is affected by the logging interval of the accelerometer, five data sets from goat G1 wearing the chest belt were used. The initial logging interval was 1 s, and through *ex post* data elimination the logging interval was gradually increased to 20 s. For each of these intervals, a new calibration data set was generated and the newly assigned activities were compared to the observed values.
(iv) To test whether the characteristics of the individual goat or the animal husbandry system (goat breed; slightly undulating or mountainous terrain; fenced or herded grazing have an effect on the quality of automated activity classification, all data sets from goats G1 and G2 when wearing the dog harness were merged and used as calibration data set for the

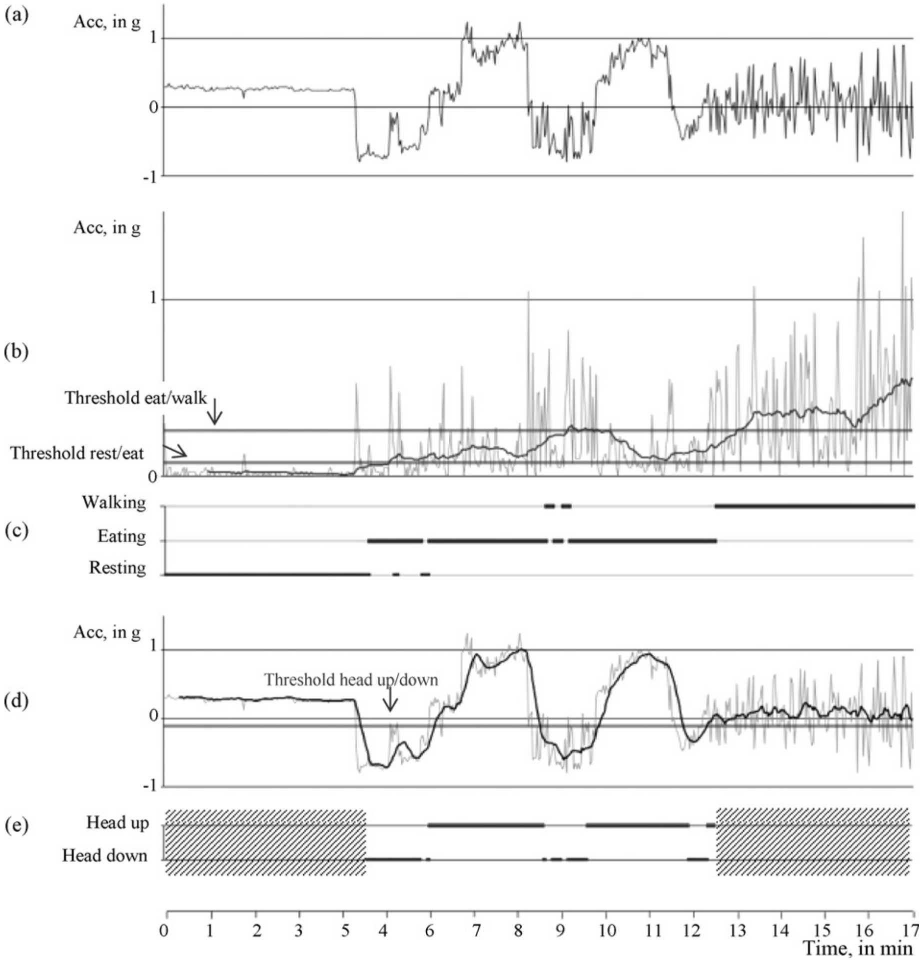

Fig. 2. (a) Raw data readout of the dynamic acceleration (acc; in units of gravity, g) of axis *X* of the Hobo® Pendant G accelerometer fixed onto a dog harness as obtained during 15 min of recording on a goat monitored in Oman. (b) Amplitude of *X*-impulses transformed into the values $dval_n$ (Eq. (5), thin line) and moving averages mav_n (Eq. (4), bold line) as well as lower and upper *X*-value thresholds separating 'resting' from 'eating' and 'eating' from 'walking'. (c) Temporal distribution of resting, eating and walking according to the classification resulting from the thresholds shown in (b). (d) Amplitude of untransformed *X*-impulses (thin line) during the eating period and moving averages mav_n (Eq. (8), bold line) separated by the threshold between head-down and head-up (Eq. (7)). (e) Temporal distribution of the goat's head posture as derived from the information on inclination of *X*-values shown in (d).

classification of activities of the dog harness-wearing goat O (7 days × 10 h registries) and *vice versa*. Thereby, only every second accelerometer registry was kept in the merged G1_G2 data set (5 days × 4 h registries), so as to adjust the 1 s logging interval applied in Germany to the 2 s logging interval used in Oman.

(v) To test the reliability of the automated system for recognition of head-up and head–down positions, the Oman data was used. Out of the seven daily data sets from the dog harness-wearing goat O, four data sets were used for calibration and the remaining three for validation. The test was repeated three times, whereby each time randomly selected data sets were combined: sets O_1, O_2, O_3, O_4 constituted the first calibration data set; sets O_4, O_5, O_6, O_7 constituted the second and sets O_2, O_4, O_5, O_7 the third calibration data set, with the remaining data sets always being used for the respective validation.

Table 2
Comparison of the results obtained for the lower and upper threshold values (expressed in gravity, g) separating the activity 'resting' from 'eating' and 'eating' from 'walking', respectively, for a neck collar (C), a chest belt (B) and a dog harness (H) used simultaneously for mounting the logger on one goat during three consecutive days. Measurements lasted 4 h each, which at a logging interval of 1 s resulted in 14,400 records for each data set.

Data set (see Table 1)	Threshold values (g)					
	X-axis		*Y*-axis		*Z*-axis	
	Lower	Upper	Lower	Upper	Lower	Upper
7_G1_C	0.106	0.276	0.115	0.48	0.098	0.368
7_G1_H	0.061	0.186	0.075	0.295	0.048	0.273
8_G1_C	0.089	0.294	0.116	0.411	0.097	0.367
8_G1_B	0.029	0.119	0.041	0.201	0.031	0.086
9_G1_H	0.06	0.22	0.055	0.255	0.039	0.159
9_G1_B	0.035	0.165	0.057	0.282	0.032	0.122

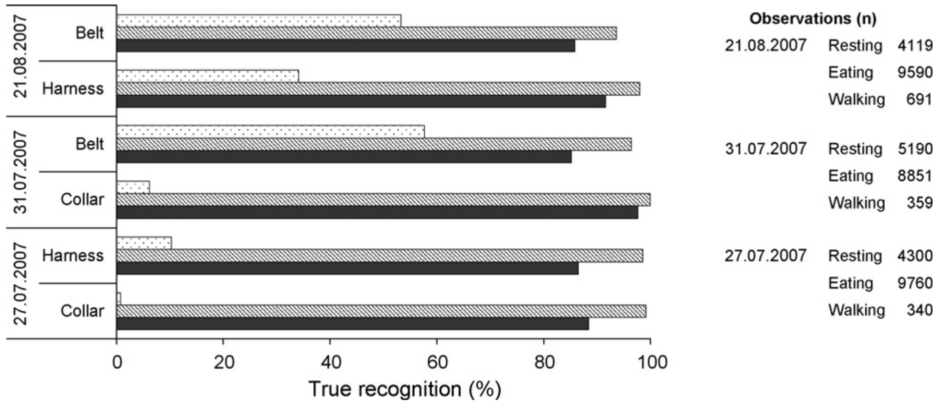

Fig. 3. Effect of the logger mounting system (chest belt, dog harness or neck collar) and observed number of activities (right column) on the true recognition (Eq. (9)) of the activities 'resting' (black), 'eating' (hatched) and 'walking' (dotted) through the automated classification of accelerometer data using the custom-made 'Animstat' software tool. Data sets are described in Table 1.

2.7. Combination of accelerometer and GPS

After the automated classification of accelerometer data from goat O, the results were merged (by time of recording) with the recordings of the GPS tracking collar, so as to determine the spatial component of the goat's activities at pasture. The resulting data were imported into ArcGIS 9.2 (ESRI, Redlands, CA, USA) and overlaid on a 3D terrain map.

3. Results

3.1. Effect of logger fixation on activity determination

Mounting the accelerometer on the collar (C), belt (B) and dog harness (H), respectively, resulted in an average deviation of the resting-eating (lower) threshold of each axis of 0.045–0.050 g between C and H, 0.060–0.075 g between C and B and 0.002–0.025 g between B and H (Table 2). For the eating-walking (upper) threshold, these ranges were 0.090–0.185 g, 0.175–0.281 g and 0.027–0.055 g. With the fixed orientation of the device in our setting relative to the animal's horizontal body axis, the average deviation of upper and lower threshold values was always lowest for the *Y*-axis and highest for the *X*-axis. Day effects of the upper and lower threshold values for any type of mounting system were negligible. Irrespective of the day and the mounting system, the true recognition (number of correctly classified activities *i*/number of observed activities *i*; Eq. (9)) of the three activities by the logger varied from 94% to 99% for eating and from 85% to 98% for resting. The recognition of walking was at maximum 58% (Fig. 3).

3.2. Comparability of activity determination between individuals

Using the dog harness for logger mounting, data from goat G1 were used to determine the lower and upper threshold values for each of the three dimensions, and these were then applied to classify data from goat G2 and *vice versa*. For the calibration data set obtained from goat G1 (28,800 records), the true recognition was 89% for resting (8419 observations), 97% for eating (19,350 observations) and 25% for walking (1031 observations), resulting in an overall true recognition (Eq. (10)) of 92%. For the validation data set from goat G2 (43,200 records), the true recognition was 87% for resting (9975 observations), 73% for eating (31,623 observations) and 45% for walking (1602 observations), yielding an overall true recognition of 75%. However, the statistical concordance (number of classified activities *i*/number of observed

Table 3
True recognition (Eqs. (9) and (10)) and statistical concordance (Eq. (11)) of goats' activities 'resting', 'eating' and 'walking' when calibrating and validating 3D dynamic acceleration data with data of two different goats (accelerometer fixed onto a chest belt).

Parameter	Parameter value	Calbration 1: data goat G1	Validation 1: data goat G2	Calibration 2: data goat G2	Validation 2: data goat G2
Observations (n)	Resting	21,573	5296	5922	23,075
	Eating	42,037	19,673	20,001	41,034
	Walking	8390	3831	2877	7891
True recognition (%)	Resting	78	68	74	79
	Eating	90	90	93	88
	Walking	77	92	86	72
	Total	85	85	87	83
Statistical concordance (%)	Resting		74		90
	Eating		101		104
	Walking		178		113

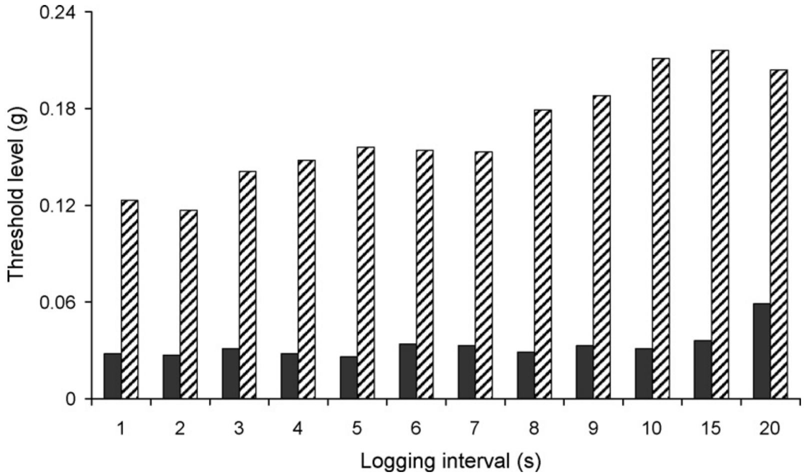

Fig. 4. Effect of the logging interval on the threshold levels (here: for the *X*-axis; unit: gravity, g) for the separation of 'resting' from 'eating' (lower threshold, black) and 'eating' from 'walking' (upper threshold, patterned) through the automated classification of accelerometer data by the custom-made 'Animstat' software tool.

activities *i*; Eq. (11)) for the validation data set showed a severe overestimation for resting (168%) but predicted well eating (79%) and walking (87%). Using the data of goat G2 for calibration and the data of goat G1 for validation, the calibration data set yielded a true recognition of 78% for resting, 95% for eating, 52% for walking and an overall true recognition of 87%; for the validation data set a true recognition of 80% for resting, 97% for eating, and 36% for walking were obtained, the overall true recognition was 90%. In this case, the statistical concordance for the validation data was 80% (resting), 109% (eating) and 98% (walking).

Repeating the test with the belt for logger mounting yielded better results (Table 3) for eating and walking but less accurate ones for resting compared to the dog harness. Likewise, the values for statistical concordance were higher for validation data sets obtained with the belt as compared to those obtained with the dog harness.

3.3. Effects of the recording interval

The stepwise increase of the accelerometer's logging interval from 1 s to 20 s lead to a concomitant reduction in data records from 72,000 to 3600. The decrease in logging frequency resulted in a gradual increase of the lower and upper threshold values obtained for the axes *X* (Fig. 4), *Y* and *Z*, and decreased the precision of behaviour prediction from the accelerometer data as expressed by the true recognition and the statistical concordance (Table 4).

3.4. Logger mounting system

Due to differences in the amplitudes of the logger axes when attached to different mounting systems, the lower and upper threshold values for separating resting from eating and eating from walking were lowest for the belt, highest for the neck collar and intermediate for the dog harness. This seemed to be independent of the number of observations obtained for each mounting system: when subjecting the true recognition values from the calibration data sets (dependent variables) to an analysis of variance (SAS version 9.1, SAS Institute, Cary, NC, USA) using the mounting system as independent variable and the number of observations as co-variable, the effect of the mounting system was significant at $P < 0.01$ for the true

Table 4
Effect of time interval between subsequent loggings of tri-axial dynamic acceleration on the true recognition (Eqs. (9) and (10)) and statistical concordance (Eq. (11)) of the automated classification of the goat activities 'resting', 'eating' and 'walking' using the 'Animstat' software tool.

Logging interval (s)	Observed activities (n) used for calibration			True recognition (%)				Statistical concordance (%)		
	Resting	Eating	Walking	Resting	Eating	Walking	Overall	Resting	Eating	Walking
1	25,702	39,327	6971	78	90	77	85	84	107	120
2	12,851	19,664	3485	75	90	70	83	80	110	119
3	8,562	13,109	2329	70	91	64	81	74	114	114
4	6,425	9,830	1745	73	9	56	81	78	115	96
5	5,140	7,865	1395	69	89	60	79	73	114	119
6	4,287	6,554	1159	69	88	56	78	75	114	112
7	3,675	5,624	988	70	89	53	79	74	114	115
8	3,208	4,919	873	70	93	41	80	74	122	74
9	2,864	4,359	777	66	94	37	78	69	126	70
10	2,571	3,932	697	68	91	43	78	74	120	81
15	1,716	2,621	463	63	93	37	77	65	127	80
20	1,286	1,964	350	64	89	35	75	71	122	87

Table 5

Effect of the animal husbandry system on the quality of automated behaviour classification as reflected by the true recognition (Eq. (9) and (10)) and statistical concordance (Eq. (11)) of the activities resting, eating and walking of goats G1 and G2 (grazing fenced undulating pasture in Germany) and goat O (herded on open-access mountain pasture in Oman) equipped with a tri-axial accelerometer mounted onto a dog harness (logging rate 2 s).

Data sets (see Table 1)	Observation records (n)			True recognition (%)				Statistical concordance (%)		
	Resting	Eating	Walking	Resting	Eating	Walking	Overall	Resting	Eating	Walking
Calibration data G1_G2	9,197	25,488	1,315	83	94	21	88			
Validation data O	34,215	59,088	30,439	89	92	59	83	91	120	72
Calibration data O	34,215	59,088	30,439	89	82	81	84			
Validation data G1_G2	9,197	25,488	1,315	84	91	28	87	102	101	77

Table 6

Number of records used for classification and resulting true recognition (Eqs. (9) and (10)) and statistical concordance (Eq. (11)) of the activity eating and the two subcategories grazing (head-down) and browsing (head-up) in a herded goat equipped with a tri-axial accelerometer mounted onto a dog harness (logging rate 2 s).

Data sets[a]	Observation records (n)			True recognition (%)				Statistical concordance (%)		
	Eating	Grazing	Browsing	Eating	Grazing	Browsing	Grazing and browsing	Eating	Grazing	Browsing
Calibration data 1	34,486	17,920	16,566	81	71	76	74			
Validation data 1	24,602	9,808	14,794	84	64	82	75	102	88	111
Calibration data 2	33,326	15,541	17,785	83	68	80	74			
Validation data 2	25,762	12,187	13,575	82	71	75	73	95	90	99
Calibration data 3	33,012	17,515	15,497	82	69	79	74			
Validation data 3	26,076	10,213	15,863	78	62	76	70	89	79	95

[a] Calibration data: set 1: O_1, O_2, O_3, O_4; set 2: O_4, O_5, O_6, O_7; set 3: O_2, O_4, O_5, O_7; Validation data: set 1: O_5, O_6, O_7; set 2: O_1, O_2, O_3; set 3: O_1, O_3, O_6; for individual data sets see Table 1.

recognition of resting, eating and walking was well as for the overall true recognition. This indicates that the same mounting system must be used for the collection of the calibration and the application data. The number of observations significantly influenced the true recognition of resting ($P = 0.03$), eating ($P = 0.007$) and walking ($P < 0.001$) but was insignificant for the overall true recognition.

3.5. Concordance of classification across individual goats and goat husbandry systems

For the validation data set from goat O (123,742 records), the true recognition was >88% for resting and eating, and even for walking a value close to 60% was obtained (Table 5). For the combined G1_G2 validation data set (36,000 records) the true recognition of resting and eating was >83%, while

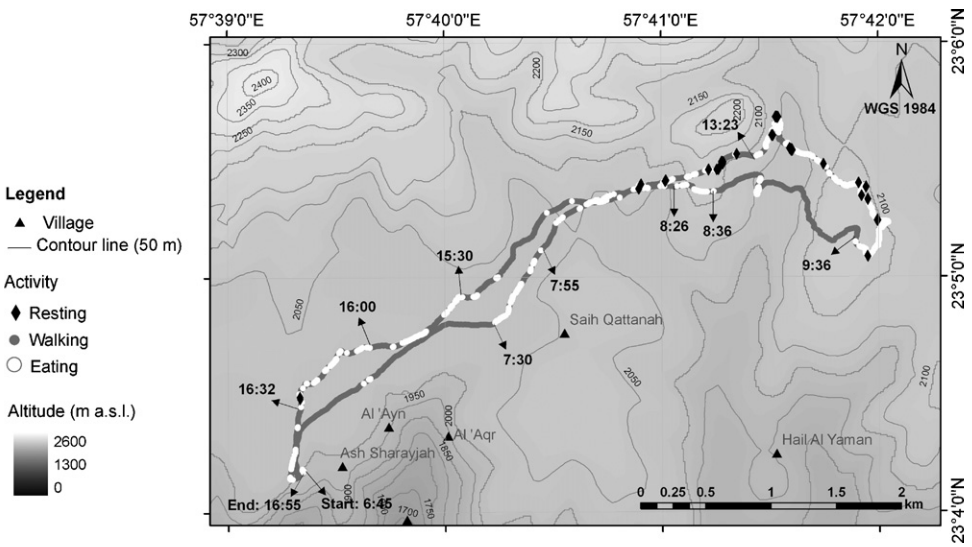

Fig. 5. Spatial distribution of the day-time activity of a goat from the village of Ash Sharayjah herded on communal pasture on the Al Jabal al Akhdar Mountain Plateau, Oman, as derived from the combination of accelerometer and GPS data and overlay on a digital elevation model.

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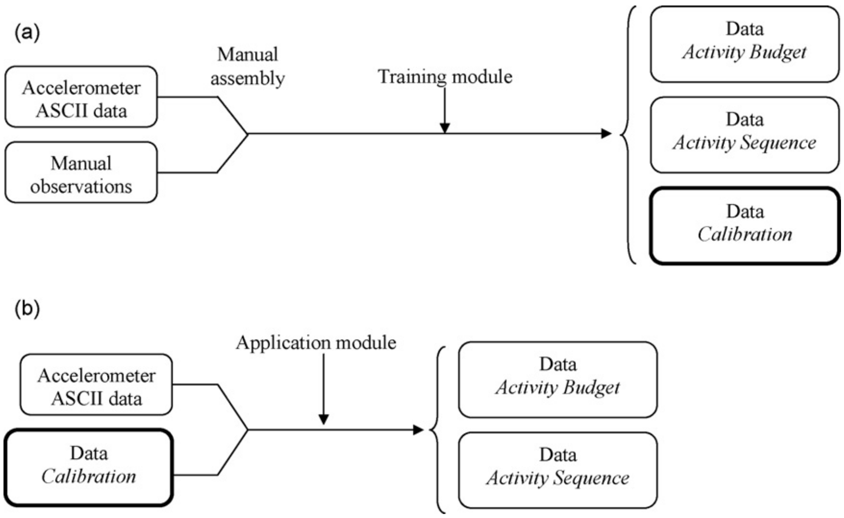

Fig. 6. Processing of accelerometer data with the calibration (training) module (a) and the analysis (application) module (b) of the 'Animstat' software tool, and resulting output files.

the true recognition of walking was 28%. As far as the statistical concordance is concerned, using the Oman data for validation yielded a satisfying result for resting (91%) but overestimated eating (120%) and underestimated walking (72%); when the German data set was used for validation, a statistical concordance of nearly 100% was obtained for resting and eating compared to 77% for walking.

3.6. Determination of head position

For the three calibration data sets obtained with the dog harness (Table 1), the true recognition of head-up positions was always >75%, while values for head-down positions varied between 68% and 71%. For the respective validation data sets, the true recognition for head-up was again >75% but was only between 61% and 71% for head-down (Table 6).

3.7. Combining accelerometer and GPS recordings

Leaving the homestead at 6:45 a.m. daily, our test goat first grazed for about 25 min on the pasture area near Sayh Qatanah (7:30 a.m.); a second grazing bout of approximately 10 minutes was observed along the road running from Sayh to Birkat al Mawz, starting at 8:46 a.m. The major grazing period, interrupted by short walking and resting bouts, started at 9:36 a.m. and ended at 1:23 p.m. On the way back to the homestead, several shorter resting and especially grazing bouts were recorded (Fig. 5).

4. Discussion and conclusions

In combination with the data analysis tool 'Animstat', the tri-axial accelerometer tested in this study proved to be a useful tool for the automated determination of major activities of goats at pasture. In contrast to visual classification of accelerometer data (Van Oort et al., 2004; Yoda et al., 2001) or explorative calculation of threshold values for accelerometers (Müller and Schrader, 2003) and pedometers (Champion et al., 1997) adjusted per animal and sometimes even per day (Müller and Schrader, 2003; Van Oort et al., 2004), our setup limits the need for human observation of animals and visual inspection of data to the calibration phase of the software programme for the specific setting of a study (animal species, logger mounting system, logging interval, terrain and vegetation conditions, husbandry system).

4.1. Reliability of automated classification

The classified accelerometer data characterizes the temporal organization of the goats' major activities at pasture and allows calculating hourly and daily time budgets for each activity. For 10 of the 11 validation data sets, the true recognition of eating and resting were >73% and <97%. For walking, the true recognition was < 80% in 2 and >120% in 3 out of the 11 validation data sets. These results are related to several factors. Firstly, the time interval for the direct observation and manual recording of the goats' activities was 10 s, while the logging interval of the accelerometer was 1 s or 2 s. As activity changes in goats can occur quite abruptly, these may not always have been detected by the observer. This will affect the quality of the calibration run of the accelerometer data in the 'Animstat' software and consequently affect the quality of activity prediction for unobserved recordings. Secondly, the programme's procedure of calculating moving averages (Eq. (4)) modifies the amplitude of the accelerometer readings. If a goat's activity abruptly changes from resting to walking, the software, through the moving average, may identify an intermediate – and faulty – period of eating. This first and second source of erroneous activity classification can only be overcome by continuous activity observation or videotaping with subsequent transcription of scenes. Both approaches are, however, very tedious and, depending on the terrain type, may even be impossible to follow. From a practical point of view, even for goats with their compared to cattle much more abrupt changes in activity, recording intervals <5 s seem irrelevant. The use

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of this accelerometer for recording the grazing activity of other species such as cattle or camels would require proper calibration and most likely allow using wider intervals given the more deliberate movements of these species. At a 5 s interval, our accelerometer would allow continuous activity recording for 30 h. However, more stringent testing of the impact of the logging interval on the quality of the automated classification of accelerometer data is needed before firm recommendations can be given concerning this aspect.

The third source of erroneous activity classification is related to the software's optimization routine used to determine, for each of the three axes, the most appropriate lower and upper threshold and number of individual recordings per moving average (Eq. (2)). This routine represents a compromise between a maximization of the true recognition for each single activity (Eq. (9)) on the one hand and a maximization of the overall true recognition across all activities (Eq. (10)) on the other hand. Given the unequal number of observations for the different activities, a maximization of the true recognition of specific activities (resting, eating, walking) cannot be achieved in parallel to a maximisation of the overall true recognition. This third source of error is thus a systematic problem that cannot be overcome as long as the number of observations differs for the specific activities. Further studies must therefore determine the minimum number of observations needed in a calibration data set to obtain an accuracy >90% in the automated classification of a specific activity. Since the two maximisation routines that the program offers have different objectives (see above), the 'Animstat' maximization routine has to be selected *a priori*.

Our results indicate that if sufficiently large calibration data sets are available, a calibration established from data recorded with one individual can be used to classify the activities of another individual, and this even across goat breeds and husbandry systems. However, if studies are planned with several animals, the calibration data set should also be based upon observation of several individuals.

As has been demonstrated by the mathematical increase in the logging interval, a high precision of data classification requires also a relatively short logging interval. However, the latter also depends on the ease of reading out the accelerometer on a one- or two-day basis. From the above it is self-evident that the logging interval should remain unchanged throughout the calibration and the application phase of an experimental series.

4.2. Effects of logger mounting system

Due to the head movements, the accelerometer registers much more weak-amplitude movements when fixed on the animal's neck than on its body. The amplitudes obtained when mounting the accelerometer on the dog harness were in-between the two other mounting systems. Since with the dog harness the logger is placed on the withers, each head movement is reflected in an inclination of the X-axis and can thus be used to satisfactorily distinguish grazing from browsing. Fixing the accelerometer on the neck seems even more appropriate for detecting head-up and head-down positions, but larger calibration data sets than the ones compiled in our study would be necessary to verify this hypothesis. For unambiguous classification of head position, the orientation of the three accelerometer axes relative to the animal's body should always be the same. If the three axes are oriented differently from the proposition used in this study, the vertical axis, which defines head position, has to be re-defined in the 'Animstat' program (Eqs. (6)–(8)).

4.3. Combining accelerometer and GPS

Equipping a single animal simultaneously with several recording devices has certain disadvantages: with increasing weight of the equipment, the animal may become more quickly exhausted, which likely influences its activity patterns (Blanc and Brelurut, 1997; Rutter et al., 1997; Müller and Schrader, 2003). In addition, the multiplication of information obviously renders data analysis heavier (Howell and Paice, 1989). However, various studies show that the combination of devices with one or more accelerometers enables a better understanding of the characteristics of an activity: in humans, Knight et al. (2007) associated an accelerometer with a heart-rate sensor; in marine animals, accelerometers were combined with depth sensors (Arai et al., 2000; Yoda et al., 2001). In this study, we combined the accelerometer with a GPS tracking collar whereby at approximately 700 g, the total weight of the two devices was <2% of the body weight of goat O and thus acceptable for the animal (Blanc and Brelurut, 1997). The combination of these two devices allowed recording the spatio-temporal activity of goats at pasture; from this, areas characterized as high pressure zones according to formerly collected GPS tracking data (Schlecht et al., 2009) could now be differentiated into grazed zones and areas only affected by trampling but not by grazing. Such insights into pasture use are only obtained through the combined use of a GPS with a high-resolution accelerometer. During the last years, a variety of GPS tracking devices have appeared on the market that allow such joint recording of position and activity (Lotek Wireless, Newmarket, ON, Canada; Aerospace GmbH, Berlin, Germany; BlueSky Telemetry, Aberfeldy, Scotland). Tests of some of the devices showed their usefulness for behaviour studies in ruminants (Ungar et al., 2005). In very rugged terrain however, some devices are only operational to some extent (Buerkert and Schlecht, 2009). As these devices are moreover rather expensive, our aim was to combine a lightweight standard GPS with an inexpensive tri-axial accelerometer to provide a low-cost alternative with high spatio-temporal resolution.

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Appendix A

A.1. Principles of the automated activity classification programme 'Animstat' used to convert accelerometer data into behavioural classes

The automated classification of activity records is based on the different activity levels of animals leading to different amplitudes in the 3D space. Since the logging interval was very short (1 s or 2 s) it was necessary to consider moving averages of several measurements to define the activity, such as to avoid misclassifications due to head shaking or chasing of insects. The major task of the optimization routine in the training module is to detect, for each of the three dimensions, the most appropriate threshold levels and number of individual recordings per moving average, which indicate the change from one activity to another, and thus guarantee a maximum agreement of assigned classification to the observed animal behaviour. The optimization is performed for each dimension (*X*, *Y* and *Z*) separately and is based on a maximization of a sum of scores *sumS* computed as:

$$sumS = \sum_{n=1}^{nrec} S_n \tag{1}$$

where *nrec* is the total number of data records in the training data set and S_n is a score for record *n* computed as

$$S_n = \begin{cases} 1 - \left(\dfrac{nobs\_rest}{nrec}\right) & \text{if record } n \text{ is classified as resting and the classification is correct} \\ 1 - \left(\dfrac{nobs\_eat}{nrec}\right) & \text{if record } n \text{ is classified as eating and the classification is correct} \\ 1 - \left(\dfrac{nobs\_walk}{nrec}\right) & \text{if record } n \text{ is classified as walking and the classification is correct} \\ 0 & \text{if the classification is wrong} \end{cases} \tag{2}$$

where *nobs_rest* is the total number of resting observations in the training data set, *nobs_eat* is the total number of eating observations in the training data set and *nobs_walk* is the total number of walking observations in the training data set. This procedure ensures that the correct classification of less frequent observations gets a higher weight than a correct classification of more frequent observations. The decision how a record is classified depends on the following criteria:

$$\begin{array}{lll} classi\,fication = \text{'resting'} & \text{if} & mav_n < t\_re \\ classi\,fication = \text{'eating'l} & \text{if} & t\_re \le mav_n \le t\_ew \\ classi\,fication = \text{'walking'} & \text{if} & t\_ew < mav_n \end{array} \tag{3}$$

where mav_n is the moving average of impulse changes at record *n*, *t_re* is the threshold between resting and eating (lower threshold) and *t_ew* is the threshold between eating and walking (upper threshold). The thresholds *t_re* and *t_ew* are allowed to vary in steps of 0.001 g between 0 g and 6 g, whereby *t_ew* has always to be larger than *t_re*. The moving average of values at record *n* are computed as

$$mav_n = \frac{dl_{n-m} + \cdots + dl_n + \cdots + dl_{n+m}}{2m+1} \tag{4}$$

with

$$dl_n = \sqrt{(l_n - l_{n-1})^2} \tag{5}$$

where val_n is the value for the impulse in the actual dimension (*X*, *Y* or *Z*) and record *n*, val_{n-1} is the value for the impulse in the actual dimension (*X*, *Y* or *Z*) and record $n-1$, $dval_n$ is the absolute difference between val_n and val_{n-1}, and $m = \{1, 2, \ldots, 15\}$.

For each dimension, *sumS* is computed for all possible combinations of *m*, *t_re* and *t_ew*, and the combination where *sumS* is maximal is considered to be the optimum. This optimal combination is used to classify the activity records in the training data set into resting, eating or walking, resulting in one classification for each dimension and record. The final classification is based on the majority of the classification decisions in the specific dimensions. If, for example, according to the *X*- and *Y*-dimension an activity record is classified as eating and according to the *Z*-dimension the record is classified as walking, the final decision is eating. If the classification is different in all three dimensions, the record is classified according to the classification in the dimension with the largest value for *sumS*. Together with the results from the classification of the head position (see below), the classification results are stored in the output file named 'Activity Sequence' (Fig. 6). A second output file named 'Activity Budget' summarizes the number of classified records for each activity.

In a second step, all records classified before as eating are further subdivided into the classes 'grazing' (head-down) or 'browsing' (head-up). Similar to equation 1 the automated classification is based on a search for the maximum of *sumS*, thereby only referring to the X-axis records. In this second step, S_n is computed as

$$S_n = \begin{cases} 1 - \left(\dfrac{nobs\_gr}{nobs\_eat}\right) & \text{if record } n \text{ is classified as 'grazing' and the classification is correct} \\ 1 - \left(\dfrac{nobs\_br}{nobs\_eat}\right) & \text{if record } n \text{ is classified as 'browsing' and the classification is correct} \\ 0 & \text{if the classification is wrong} \end{cases} \tag{6}$$

where *nobs_gr* is the total number of grazing observations in the training data set and *nobs_br* is the total number of browsing observations in the training data set. The decision how a record is classified depends on the following criteria:

$$\begin{array}{lll} classification = \text{'gr'} & \text{if} & mav_n < t\_gb \\ classification = \text{'br'} & \text{else} & \end{array} \quad (7)$$

where *t_gb* is the threshold between 'grazing' and 'browsing'. The values for *t_gb* may vary between −3 g and 3 g. The moving average of values at record *n* is computed as

$$mav_n = \frac{X_{n-m} + \cdots + X_n + \cdots + X_{n+m}}{2m+1} \quad (8)$$

where X_n is the value for X and record n, X_{n-m} is the value for X and record m and $m = \{1, 2, \ldots, 15\}$. Since moving averages are computed here from the X-axis records directly and not from absolute changes in X-axis records, the moving averages mav_n and the related threshold *t_gb* may become negative. The value *sumS* is computed for all possible combinations of m and *t_gb*, and the optimum is reached where *sumS* is maximized. This optimal combination is then used to classify the eating records in the training data set into 'grazing' or 'browsing'.

The nine parameters defined in the training module are stored in a file named 'Calibration', which is subsequently used as input in the application module (Fig. 6) to attribute an activity to single records of unobserved accelerometer data according to the routines described above.

A.2. Quality assessment of the automated classification

During data processing in the training module, a file named training_stats.txt is created in order to determine the precision of the automated classification of activities. For each activity i (with i = resting, eating or walking) and for each position j of the head (with j = head-down or head-up), this file reports the number of manual observations (obs_i; obs_{ij} for eating), the number of attributed activities corresponding correctly to the manual observation (cor_i; cor_{ij}) and the overall number of attributed activities i ($stat_i$; $stat_{ij}$). On the basis of these values, two different ratios characterising the precision of the classification are calculated: the true recognition of each activity i (TR_i), and the statistical concordance between the attributed and the observed activities (CS_i). Additionally, the overall true recognition (TR_{tot}) is computed as the overall percentage of correctly attributed activities.

True recognition, per activity i:

$$\mathrm{TR_i} = \frac{cor_i}{obs_i} \times 100 \quad (9)$$

True recognition, overall:

$$TR_{tot} = \frac{\sum_{i=1}^{3} cor_i}{\sum_{i=1}^{3} obs_i} \times 100 \quad (10)$$

Statistical concordance:

$$CS_i = \frac{stat_i}{obs_i} \times 100 \quad (11)$$

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