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Identification of five brown bear (*Ursus arctos*) behaviors using tri-axial accelerometers

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Master thesis

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Photo and illustrations: Gunn Elisabeth Sydtveit Rekvik

Preface

This thesis is a part of the master program at Telemark University Collage, Norway. The plan is to publish my study in PLOS ONE and I have therefore written the paper in that style. The research was founded by Telemark University College, Norway.

I would specially thank my husband and my two boys, which have been very interested in my work and motivated me. Thanks to all zoo-keepers at Bjørneparken in Flå fall 2014, for their compassion for their work with the bears. You have all been an inspiration for me!

Abstract

Bio-logging as a technique for studying animal behavior is a growing field, and small devices, such as tri-axial accelerometers, reveal a more complex picture of an animal's behavior and ecology. This is particularly important for shy or elusive species that are hard to observe in the wild. Tri-axial accelerometers have been successfully deployed on a range of animal species, however studies on large carnivores are rare. Here I investigated the suitability of using tri-axial accelerometers for detecting behaviors in brown bears (*Ursus arctos*). I also investigated if lowering the sampling frequency of the accelerometers from 40 Hz to 20 Hz, 10 Hz and 5 Hz, had an effect on the detection of behaviors. By using lower sampling frequency, it will reduce the amount of data collected and can have an impact of the batteries lifetime. Two captive bears were equipped with the accelerometer units attached to a collar. These collars stayed on for 14 days during which the bears were videotaped to be able to correlate behaviors with the acceleration data. Five behaviors were investigated: sleeping, standing, walking, feeding, and tree-rubbing. A random forest model for classifying these five behaviors by using data sets sampled with the four different sampling frequencies showed high accuracy (93-94%) in all frequencies. Thus, I concluded that this method is useful for studying animal behavior and is suitable for use on a wide range of animals, especially species that are elusive, forest dwelling, or those that move great distances (such as many large carnivore species).

Introduction

For millennia, humans have relied on gaining knowledge of an animal's behavior for survival. Today, this has changed to the opposite: knowledge of animal behavior is critically important for e.g., species conservation but also pest control (1, 2). However, often a lack of information and knowledge about species with conservation issues makes it difficult to understand animal populations, their trends, but also individual behavioral differences (3, 4). To understand a species' behavior, traditionally observational studies have been conducted by visually observing individuals and noting its movement and behavior at any particular time (5). However, observational studies of animals in the field are often are very difficult: the habitat must be open or at least semi-open, a high level of manpower is necessary, difficulties to keep track of mobile and long-ranging species, radio tracking equipment may be expensive and/or limited in its use by the landscape or habitat, and the time for studying the animal is limited to daylight hours. Moreover, direct observations may also disturb the animal and affects its behavior (6). Animal behavior is therefore often difficult and expensive to investigate, especially in species that are elusive, forest dwelling, or those that move great distances (7, 8).

Bio-logging technology has been developed to continuously monitor animal behavior where direct observations are hard or impossible (4, 9). Rutz and Hays (2009) defined bio-logging as the use of miniaturized animal-attached tags for logging and/or relaying of data about an animal's movements, behavior, physiology, and/or environment. Bio-logging studies, such as those using GPS (global position systems) for tracking movements, have increased in the last decade. Today, the use of miniature, lightweight devices, such as accelerometers, in behavioral studies is common (9).

The use of tri-axial accelerometers to study the behavior and three-dimensional

movements of wild animals avoids many of the problems of traditional behavioral observations (see above) and reduces the direct disturbance. This method was first developed to investigate diving behavior in seabirds (10). Tri-axial accelerometers record changes in velocity with respect to the earth's gravitational field; attached on an animal, these changes can be related to body movement in three directions, along the dorsal-ventral (heave), the anterior-posterior (surge) and the lateral axis (sway). Thus, accelerometers allow for identifying behavioral patterns by relating the movement-coded acceleration signal to actual behaviors (e.g. through control observations) (11, 12). In addition to the acceleration measurements, the device can measure temperature, pressure and light sensibility. It is thus even possible to investigate the metabolic rate of different activities through a movement-based proxy for energy expenditure, the overall dynamic body acceleration (ODBA) (13). The sampling frequency for accelerometry data used in different studies varies from a rather low sampling rate such as 1 Hz (1 measurement per second), which allowed to distinguish activities such as resting, eating and walking in goats (*Capra aegagrus hircus*) (14), to very high sampling rates, such as 320 Hz, for walking, feeding, bathing and swaying behaviors in African elephants (*Loxodonta africana*) (15). Previous research using accelerometers involves deployments on a range of marine (10, 16, 17) and terrestrial species (14, 18, 19), both in captivity (15, 20) and in the wild (21, 22). Despite the growing number of publications in this field, only a relative small number of studies have been carried out on large carnivores. Tri-axial accelerometers have been used to calculate the energetic cost of running in pumas (*Puma concolor*) (21), bi-axial accelerometers have been deployed on cheetahs (*Acinonyx jubatus*) to investigate feeding behavior (23) and on brown bears (*Ursus arctos*) to differentiate whether an animal was active or passive (8).

The brown bear is a solitary carnivore roaming over large areas, with male home ranges (on average 833-1055 km^2) being larger than female ones (on average 217-280 km^2)

(24). Brown bears require a large storage of fat due to hibernation for 5-7 months per year (25), which forces the animals to spend most of their daily activity in summer and fall on feeding (26). Behaviors for scent marking communication, like tree rubbing, occur in both sexes, but in male bears it occurs throughout the year and has been suggested to facilitate the communication of dominance between adult males (27) (28). Brown bears are more nocturnal and shyer in areas with higher human population densities (29), which makes the animal hard to observe in the wild. One of the biggest problems in bear management is that people are afraid of bears (30, 31), more information and understanding of bear behavior is thus a good management strategy to reduce peoples' fear (32).

The goal of this study was (a) to investigate the potential of tri-axial accelerometers for determining behavior in a large carnivore, the brown bear, and (b) to investigate the effect of decreasing the sampling frequency in the accelerometers from 40 Hz to 20 Hz, 10 Hz, and 5 Hz. I selected five behaviors for investigation: sleeping, standing, walking, feeding, and tree rubbing. Even though some behaviors may be triggered by routines in the zoo, using captive animals as surrogate allows for constructing a behavioral classification module for the acceleration data (33). To my knowledge, this is the first study using tri-axial acceleration data for investigating a range of brown bear behaviors.

Materials and Methods

Study area and study animals

The study was carried out between September 8 - 22, 2014, on two brown bears (one male and one female) at the Bjørneparken in Flå, Norway. The female was 2.5 years old with a weight of 145 kg, the male was 4.5 years old and weighted 200 kg. Both individuals shared their respective enclosure with a conspecific of the same sex. In general, bears at Flå Bearpark

are housed in three separate enclosures, located next to each other, but of different size, shape, and appearance. Both study animals stayed in all three enclosures at some point during the study, but were always separate from each other. They were moved between enclosures using gates. The smallest enclosure (732 square meters), was located on a slope with some rock formations and with water running through (Fig. 1). The medium enclosure (2243 square meters) (Fig. 2) was connected with the smallest enclosure through the den and was located on a slope with some rock formations and a small pond. Additionally, a set of big logs was installed which the bears regularly used for climbing activities. The largest enclosure (13 482 square meters) featured a large amount of vegetation, resembling a natural pine forest (Fig. 3). It was located on a slope and included some particularly steep parts.

Sedation of bears and attachment of acceleration data loggers

The bears were sedated using a dart gun (Daninject®) with a mixture of medetomidine (0.5 mg/kg) and tiletamine-zolazepam (2.5 mg/kg) (34). After finishing handling and tagging procedures, we used atipamezole (0.25 mg/kg) as antagonist (see also (34)). I used collars developed for bear radio-marking (Vectronics Aerospace, Berlin, Germany) to mount tri-axial acceleration data loggers developed by Swansea University (27x26x8 mm, weight 20g)(Fig.4) on both bears. These tri-axial acceleration data loggers recorded acceleration in all three axes with a frequency of 40 Hz and stored the data on a 1GB MicroSD-card. The data loggers were encased in epoxy resin, glued onto a short piece of the collar material, which was then bolted to the dorsal side of the collar. To prevent the collar from rotating, an empty battery pack (weighing 500 g) was attached on the ventral side of the collar (Fig. 5). The total mass of the fitted collars was 640g and 630g (0.32% and 0.43% of the body mass), respectively. Both collars were equipped with a drop-off system (Vectronics Aerospace, Berlin, Germany), which enabled us to retrieve the units without having to sedate the animals an additional time. The drop-offs for both individuals were triggered after a period of 14 days.

Control observations

Both bears were filmed with a hand-held video camera (DCR-SR35, Sony®, Tokyo, Japan) from outside their enclosure to be able to link their behavior to the acceleration data. Prior to mounting the data loggers on the bears, the time on the video camera and the accelerometers was synchronized. Video-recordings were conducted for a period of ten days (8 – 17 September), during various times of the day (ranging from 08.30 h – 22.00 h, i.e., as long as light conditions permitted filming), to capture as many observations of the different behaviors as possible. The bears were habituated to the presence of visitors outside their enclosure.

Data analysis

To avoid possible effects of the drugs and handling procedure on bear behavior, the recordings from the first day were not used for statistical analysis. After collar drop off I retrieved the collars from the enclosures. The data was downloaded to a computer, and the custom made software (Data converter, Swansea Lab for Animal Movement, Swansea University, UK) was used to convert the data from ASCII to text files. The converted files were then analyzed in Bio Visualizer (BioVis V2.222, Swansea University, UK), a novel program that allows for detecting data sequences associated with different behaviors by a template search function. To achieve a set of templates, I compared acceleration signal patterns with videotape recordings of a given behavior, and thereby was able to define a given behavior for the search template in the program. However, some behaviors may be difficult to identify by the template search function in BioVisualizer due to their complexity, and it was therefore necessary to identify and label such behaviors manually within the program. After an initial visual analysis, the following five behaviors (representing common or important brown bear behaviors) were further investigated in my analysis: sleeping (laying down, with no movements), standing (standing on four legs, no movement apart from head, due to

shifting head positions), feeding (collecting food from the ground with mouth or claws and consuming the food while standing), walking (moving forward at any speed that is not considering as running/galloping), and tree rubbing (a scent-marking behavior (28) where the bear is standing on two legs and rubs its back and head against a tree.

The frequency of the data was reduced from 40 Hz to 20 Hz by removing every second data point. The same procedure was used to reduce the sampling frequency from 20 Hz to 10 Hz, and further down to 5 Hz. Statistical analyses were conducted in R 3.1.1 (35) on mean values and standard derivations of surge, sway, and heave acceleration. All behaviors were classified using random forests (R package Random Forest). Random forests are a powerful statistical classifier for acceleration data that include variable importance measures for each predictor variable (19, 36, 37).

Ethics statement

The handling and tagging procedures were approved by the Norwegian Experimental Animal Board (ID:6366).

Results

Data collected

Both acceleration loggers recorded data for five days (8 – 12 September) before they ran out of battery. As mentioned, the first day was not used for analysis. In total for the four days used, I collected 17.5 hours of video material for the male bear, and 12 hours of video material for the female.

Four of the behaviors (sleeping, standing, feeding, and walking) occurred in long (> 20 seconds) bouts. I was thus able to cut out fifty 20 second long sequences of each of these

behaviors from both bears. This resulted in a total of 100 sequences per behavior, which permitted sufficient power for subsequent statistical tests (15). The high initial sampling frequency (40 Hz) resulted in a total of 80.000 data points for each of the four behaviors. Tree rubbing was the fifth behavior selected, even though only the male bear performed this behavior and the duration was relatively short compared with the other behaviors. Still, tree rubbing showed a very distinctive pattern and I obtained 11 sequences ranging from 6 to 52 seconds for this behavior, which resulted in a total of 11.163 data points.

Classification of behaviors

Sleeping behavior showed no appreciable temporal variation in any axis (Fig. 6a), whereas standing, feeding, walking and tree-rubbing were all characterized by oscillations in the sway axis (Fig. 6b-e). Standing behavior was characterized by small variations due to shifting of the bear's head position in sway axis and relatively bigger variations in surge axis (Fig. 6b). Walking showed high, cyclic peaks in the sway acceleration, where each peak represents a footstep (Fig. 6c). Feeding behavior also featured cyclic peaks, but clearly lower peaks than walking and small variations due to shifting in head position in sway axis and surge axis (Fig. 6d). Tree-rubbing was characterized by high peaks over 1.0 g in sway acceleration (Fig. 6e).

Analysis of five selected behaviors

Descriptive statistics (mean and standard deviation (SD)) on the accelerometer data on sleeping, standing, walking, feeding and tree rubbing for 40 Hz are presented in Table 1. Tree-rubbing had the highest standard deviation on all three axes with SD >0.587 g, and sleeping the lowest with SD <0.045 g (40 Hz values) (Table 1).

Table 1. Mean and standard deviation of the surge, sway and heave gravitational acceleration (*g*) signals for five identified brown bear behaviors (sleeping, standing, walking, feeding, and tree-rubbing) recorded with tri-axial acceleromters at 40 Hz. Behavioral sequences were selected based on video-recorded materials from a male and female brown bear, except for rubbing behavior, which was only observed rarely and in the male in this study.

Behavior	N of sequences	Sway (*g*)		Surge (*g*)		Heave (*g*)		Fig.
		$\bar{\text{x}}$	SD	$\bar{\text{x}}$	SD	$\bar{\text{x}}$	SD	
Sleeping	100	0.120	0.033	0.052	0.036	0.262	0.045	**2a**
Standing	100	0.111	0.090	-0.082	0.137	0.772	0.073	**2b**
Walking	100	0.094	0.183	0.052	0.264	0.806	0.168	**2d**
Feeding	100	0.088	0.141	0.101	0.244	0.578	0.152	**2c**
Tree-rubbing	11	-0.104	0.657	-0.067	0.626	0.058	0.587	**2e**

The random forests model classified behaviors with 95% accuracy and an out-of-bag (OOB) estimate of error rate of 5.11% for data sampled with 40 Hz (see Tab. 2). The variable importance plot for the random forest showed that the SD in general was more important than the mean for the classification of behaviors (Fig. 7). This is caused by the fact that most behaviors occur in an oscillating manner, which results in a mean acceleration value of approximately 0 *g*. The SD of the sway acceleration showed the highest variation between the different behaviors, and is therefore particularly important for behavioral classifications (Fig. 7), with sleeping having the lowest SD in the sway acceleration (SD =0.033) and tree-rubbing the highest (SD = 0.657). Standing, feeding, and walking showed lower variation of SD in the sway acceleration (0.090> SD <0.183, Tab. 1). As a result, the random forest model delivered

a higher misclassification rate for these three behaviors (Tab. 3). The multidimensional scaling plot (MDS) shows the decomposition of the proximity matrix of the random forest model, plottet and scaled down to two dimensions (Fig. 8).

Table 2. Accuracy measures for the random forest model predicting the classification of five behaviors in brown bears.

Metric		Value (%)			
		40 Hz	20 Hz	10 Hz	5 Hz
	Out-of-bag error rate	5.11	6.33	6.57	6.33
	Accuracy	94.4	94.2	93.7	93.4
Cross-validated	Cohen's Kappa	92.6	92.3	91.7	91.4

Table 3. Confusion matrix of the random forest model (Out-of-bag error rate = 5.11%) for five behaviors in brown bears (40 Hz). The table shows where misclassifications occurred and the classification error for each behavior.

	Sleeping	Standing	Walking	Feeding	Tree-rubbing	Class. Error
Sleeping	99	1	0	0	0	0.01
Standing	1	94	0	5	0	0.06
Walking	0	0	93	7	0	0.07
Feeding	0	4	3	93	0	0.07
Tree-rubbing	0	0	0	0	11	0.00

Comparison of behavioral classifications obtained with 40 Hz versus 20 Hz, 10 Hz, and 5 Hz acceleration data

Lowering the sampling frequency from 40 Hz to 20 Hz, 10 Hz, and 5 Hz did not affect the result of the behavioral classification (Tab. 2). As a visual example of lowering sampling frequency, I selected walking to show the differences when running the data through Bio Visualizer for 40 Hz, 20 Hz, 10 Hz, and 5 Hz (Fig. 9).

The random forest model showed a low OOB error rate for all four frequencies, ranging from 5.11% at 40 Hz to 6.33% at 5 Hz (for further details see Tab. 2). To test the power of the random forest model, I compared the OOB error rate with two cross-validated error measures, accuracy and Cohen's Kappa (Tab. 2). Both measures delivered precision values of over 91%, values that are considered as excellent in the literature (38, 39).

Discussion

Here I show that tri-axial accelerometers are a useful tool for identifying brown bear behaviors. The results show that data from collar-attached accelerometers can be used to distinguish the behaviors sleeping, standing, walking, feeding, and tree-rubbing.

To date, there is no common solution for matching and extracting specific behaviors from large sets of acceleration data recorded at high frequencies (as in this case 40 Hz), and several different approaches have been used (for details see (16, 19)). Here, mean and SD values for the three acceleration axes were used to build a random forest model at this stage of the evaluation of the accelerometry data (19, 22). The use of means and SD seems to be sufficient for initial analysis and evaluation if the method is useful for identifying brown bear behaviors, and at the same time these data and results provide important information which can be further used by other researchers. In general, sleeping and tree-rubbing was easily

differentiated, while there were higher misclassification between standing, walking and feeding, even so the classification error was low. In other studies using collar mounted tri-axial accelerometers the same results are shown, where some behaviors are more distinguished than other when compared. In African elephants behaviors like feeding, bathing and walking had some misclassification, but swaying showed 100 % correctly categorization (15) when compared. When comparing behaviors in badger (*Meles meles*), walking, trotting and snuffling showed some misclassification, but resting showed 100 % correctly categorization (20). The possible reasons for the classification variables shown in the random forest matrix may be due to small variations in patterns within the behavior. Sleeping was characterized with no temporal variation in the three axis, this state occurred in none of the other behaviors. Standing had no oscillation due to no movement of the body, but showing small variations due to shifting of head position in sway, surge, and heave acceleration and could be misclassified as sleeping if e.g. the head was in one position to long, or feeding if the head movement was to rapid. Walking had a characteristic pattern of cyclic peaks in sway acceleration, and the misclassification with feeding may occur when the walking was in a relatively slow pace, due to lower cyclic peaks. Feeding exhibited peaks in acceleration in all three axis, but little evidence of been cyclic through time. I would expect that misclassified as walking due to more cyclic peaks in sway acceleration in some feeding behaviors like grazing, and misclassified as standing due to less resistance in some food types that give little movements. Tree-rubbing had the highest peaks and clearly differed from the other behaviors, giving it at error rate of 0.00. In addition the random forest confusion matrix showed that in behaviors that are very distinctive, the use of a low number of sequences for training the algorithm is sufficient. All the 11 sequences for tree rubbing were classified correctly in the model.

In this study I only examined five behaviors, other behaviors will need to be added in

further studies and evaluate the further use of the pattern from the three acceleration axis. The pattern for each behavior in one species may also be used in recognition of those not yet described in others, particularly when the undescribed species have body shape that conforms roughly to that of a described animal (12).

The software used for the initial identification of the acceleration data had problems with identifying the behaviors and I had to do some identification manually. Software used for visualization and behavior identification are continuously improved at with better machine learning techniques and use of spectral analysis the handling of accelerometer data would be improved (40). In addition the possibilities and development to real-lifetime observations and remote systems in the future.

Accelerometers attached to a collar can rotate, which may result in changes of mean and standard deviation values for a particular behavior. However, the random forest classification delivered good results, even though the collars shifted position several times during the course of the study (based on visual observations). I found that collar-attached tri-axial accelerometers deliver consistent and clear data on animal behavior, something that has also been found in several other studies (15, 20). Due to the position of the logger on the bears neck, the tri-axial accelerometers can have difficulties to distinguish delicate movements collected from the anterior part of the body, e.g. the animal is holding the head/neck in same position and lowers the anterior part of the body. Other studies have pointed out this problem (41, 42).

The results from this study clearly suggest that this method can be applied to bears in the wild. However, there are some challenges to consider, such as improvement of battery life and data storage capacity. In my study, the loggers only lasted for 5 days when logging at 40 Hz, with battery lifetime being the limiting factor. Further tests to investigate if there is a positive effect on battery lifetime when lowering the sampling frequencies are recommended.

In addition, sampling data at lower frequencies would lower the amount of data collected significantly and reduce the handling time of labeling the behaviors. I investigated whether lowering the sampling frequencies to 20 Hz, 10 Hz and 5 Hz had an effect on the result. Behaviors selected in this study were clearly differentiable, and lowering the resolution from 40 Hz to 5 Hz had no impact on the classification. The accuracy measures for all four resolutions resulted in values that can be considered almost perfect results according to the literature (38, 39). Logging at 5 Hz would therefore be sufficient for identification of these five relatively "coarse" behaviors. However, I suggest to investigate if it is possible to pick up more fine scale movements and behaviors with high sampling frequency in comparison to low sampling frequency. For example, it may be possible to differentiate between different feeding behaviors, such as grazing and feeding on carcasses.

Another study using accelerometers on bears had problems in detecting behaviors like walking and grazing (feeding), due to the use of dual-axis sensors, and a method that only classified every five-minute sequence as active or passive (8). The method with the use of tri-axial accelerometers can identify between different active behaviors (walking, feeding, tree rubbing) and passive behaviors (sleeping, standing), that can be used for other research like calculating the metabolic rate of activities e.g. overall dynamic body acceleration (ODBA) (13). ODBA has shown to be a good proxy for energy expenditure in a range of animal species and humans (13, 43).

I conclude that this method is useful for studying brown bear behaviors, that this method is applicable to a wide range of animals, and that it is especially useful in species that are elusive, forest dwelling, or those that move great distances. A better understanding of brown bear behavior may aid management and conservation actions and provide useful information to reducing negative human-bear encounters or damage to livestock (3, 44).

Acknowledgement

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Fig. 1. Overview of the smallest brown bear enclosure, connected to the medium enclosure by the den, at Flå Bearpark, Norway, September 2014.

Fig. 2. Overview of the medium brown bear enclosure, featuring a small pond and installed

logs, at Flå Bearpark, Norway, September 2014.

Fig. 3. Overview of the largest brown bear enclosure, with some steep parts and natural pine forest, at Flå Bearpark, Norway, September 2014. .

Fig. 4. Tri-axial acceleration data logger (27x26x8 mm, 20g) with the battery and casing developed by Swansea University.
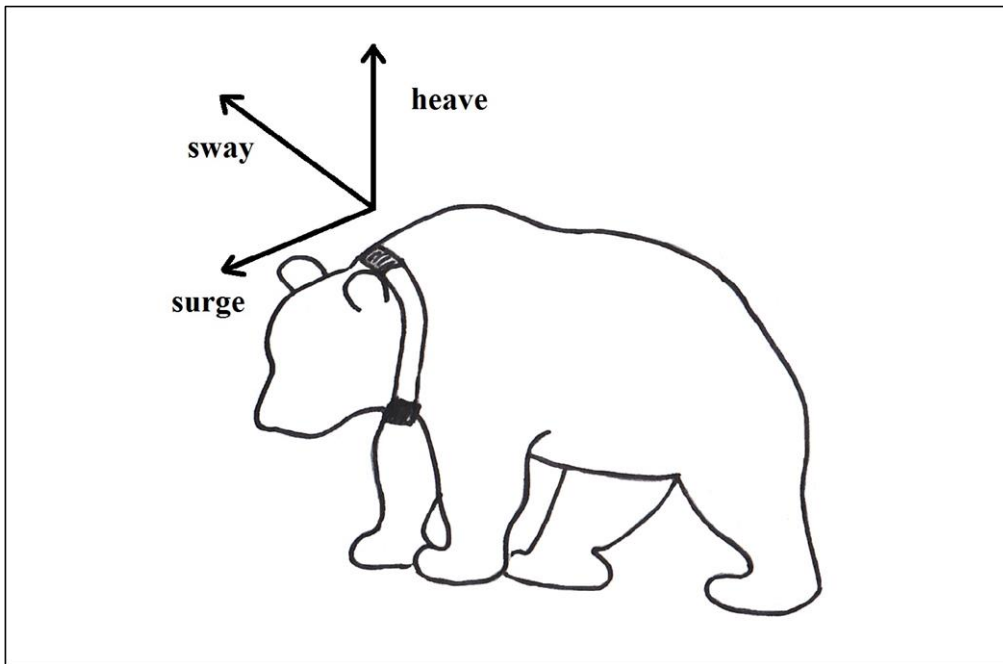
Fig. 5. The mounting and position of the acceleration unit on the dorsal side of the brown bear, with additional weight on the ventral side. The arrows indicate the possible three-dimensional movements recorded by the unit.
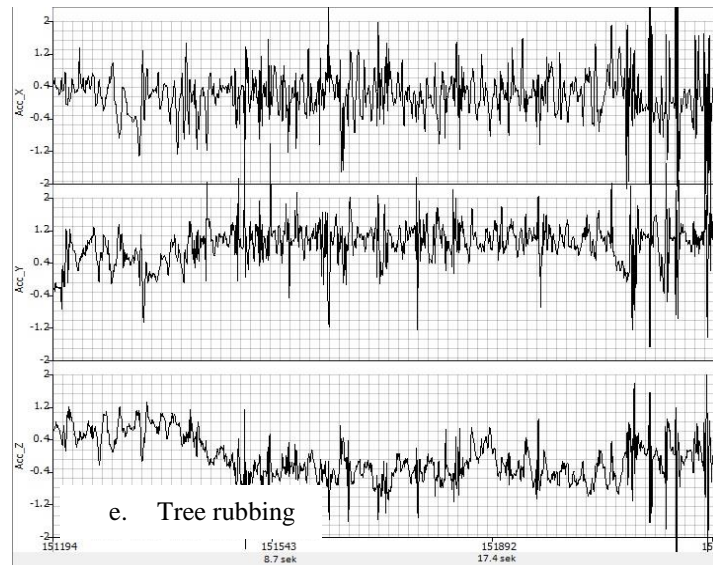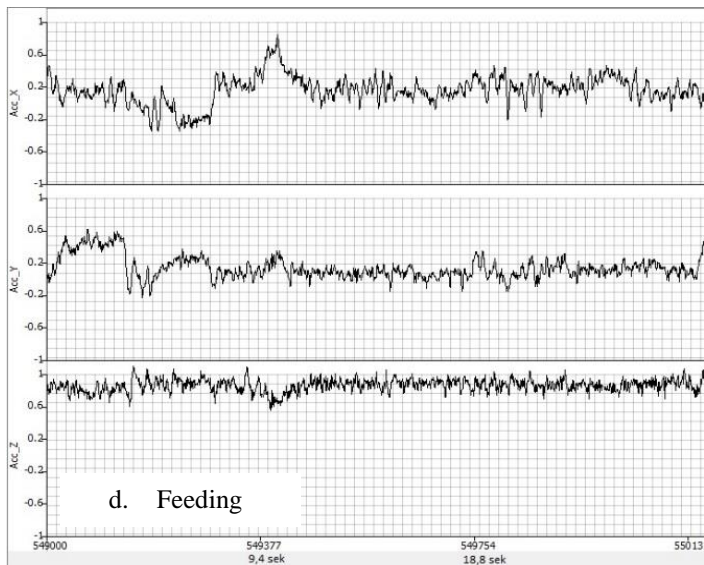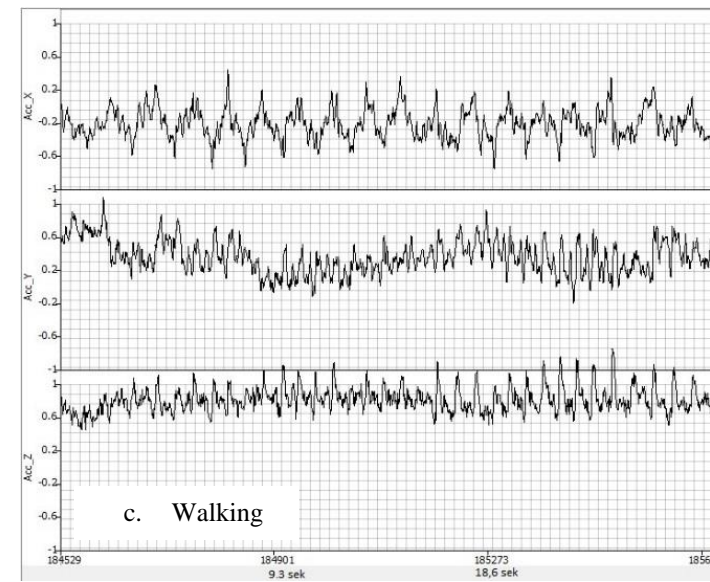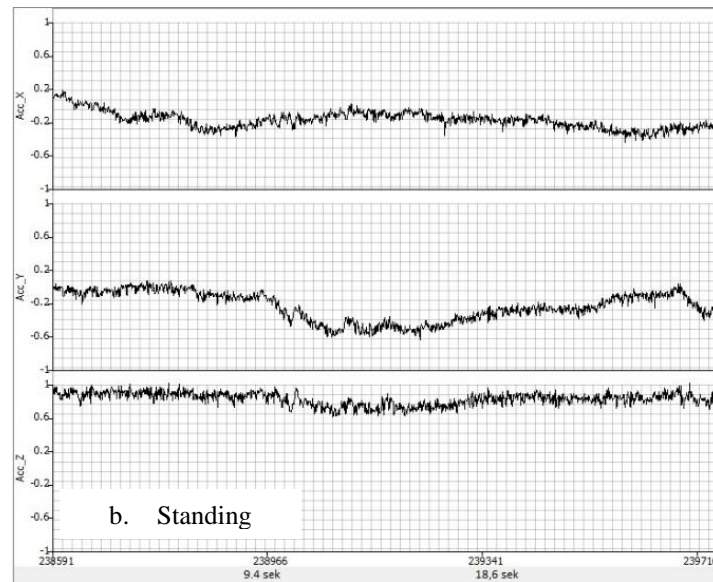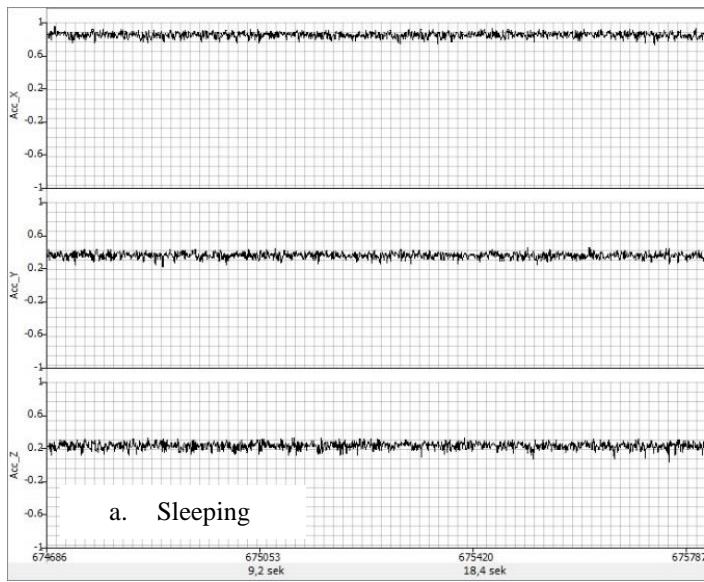
Fig. 6: Examples of the sway (Acc_X), surge (Acc_Y) and heave (Acc_Z) acceleration signals for five different brown bear behaviors logged at 40 Hz. (Because of high peaks over 1 g in the tree rubbing behavior, the axis are set between -2 and 2, instead of -1 and 1 like in the four other behaviors.)
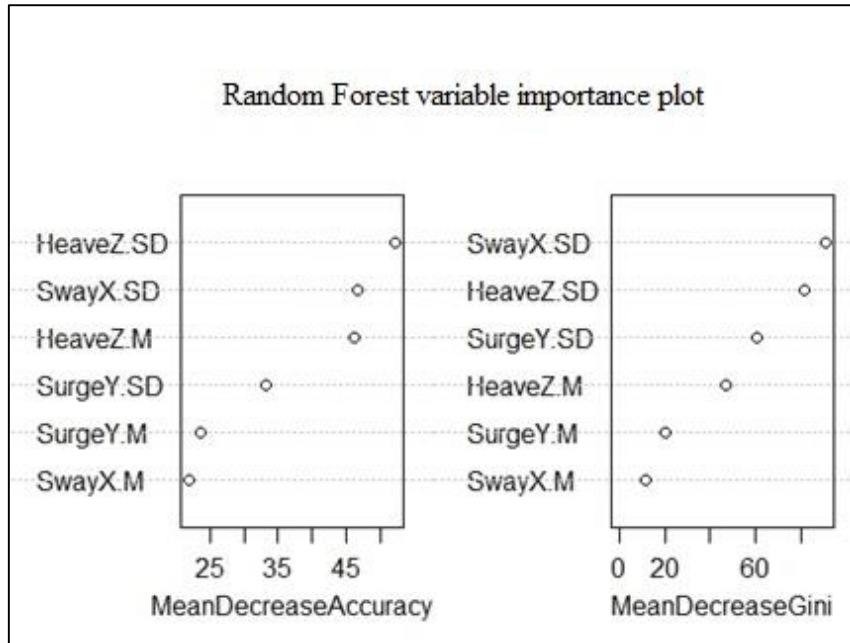
Fig. 7: Random Forest variable importance plot for five brown bear behaviors: sleeping, standing, walking, feedig and tree-rubbing at 40 Hz. Both mean decrease in accuracy (left plot) and mean decrease in the Gini index (right plot) show how important a variable is for classification. SD for standard derivation and M for mean values of sway, surge and heave acceleration values. Mean decrease in accuracy calculates how much lower a model preforms without a given variable, and mean decrease in the Gini index measures how pure the nodes are at the end of the tree. In both measurements a high score in y axis means that a given variable was important for classification.
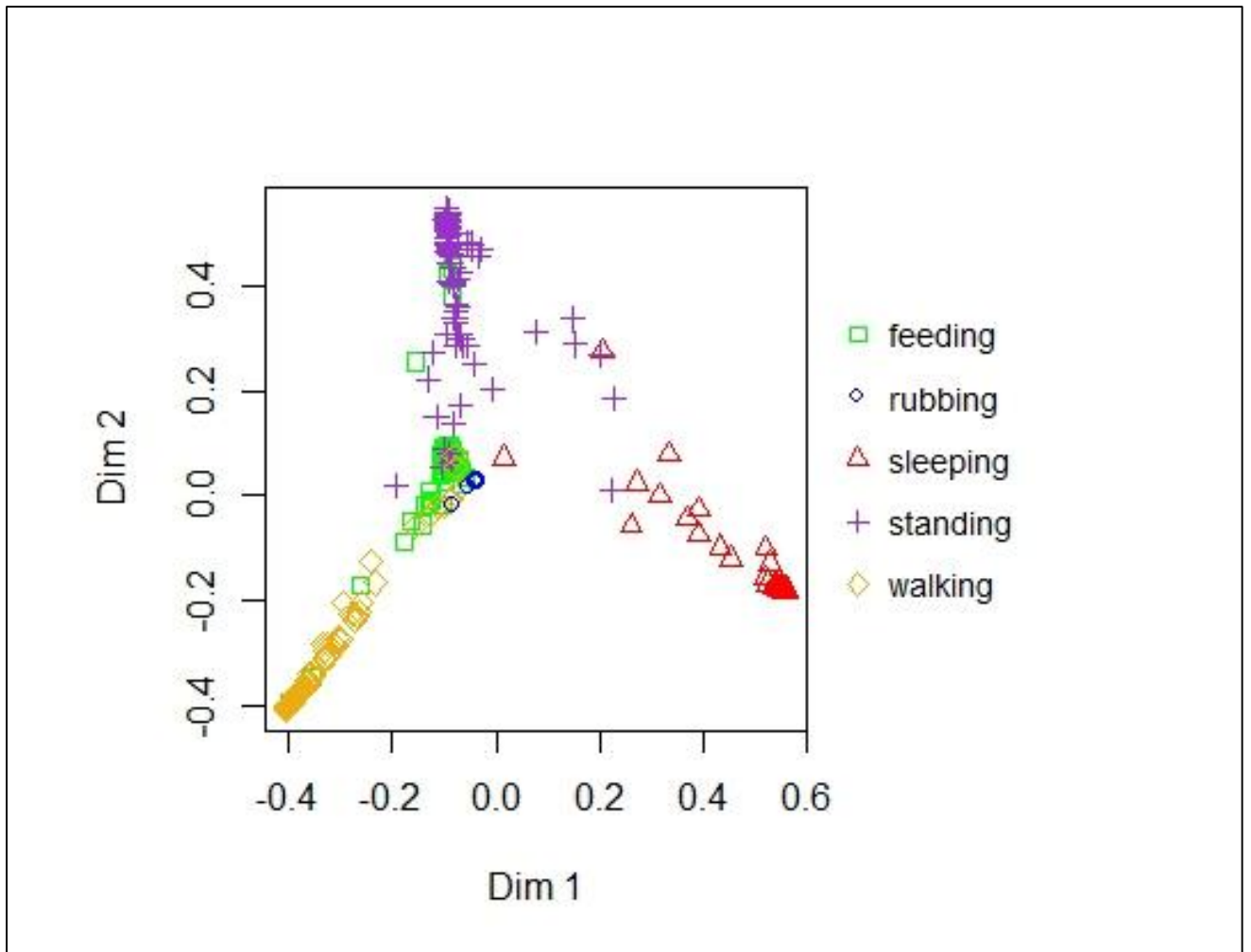
Fig. 8: Multidimensional scaling plot of the random forest classification of 5 brown bear behaviors (feeding, sleeping, standing, rubbing, walking). Here, the principal component analysis (PCA) decomposition of the proximity matrix of the random forest model is plottet and scaled down to two dimensions (Dim 1 and Dim 2).

a.   Sequence of walking at 40 Hz.   b.   Sequences of walking at 20 Hz.

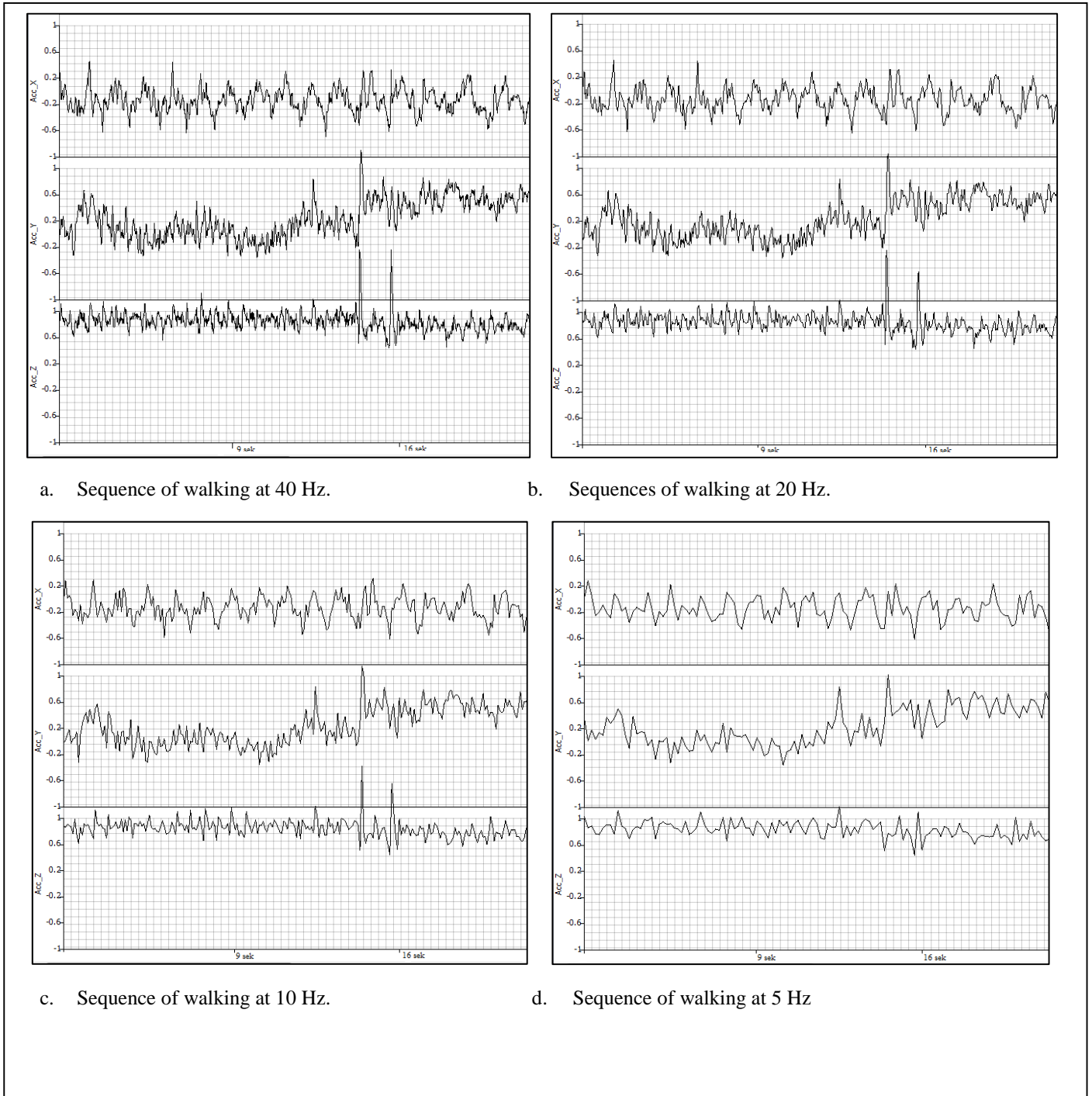c.   Sequence of walking at 10 Hz.   d.   Sequence of walking at 5 Hz

Fig 9. Example of the same sequence of walking for the sway (X), surge (Y) and heave (Z) acceleration at 40 Hz (a), 20 Hz (b), 10 Hz (c) and 5 Hz (d) resolution.