Analiza aktivnosti mrkog medvjeda (Ursus arctos Linnaeus, 1758) u prirodi i zatočeništvu

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Analyses of Brown Bear (*Ursus arctos* Linnaeus, 1758) activity in natural conditions and captivity

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Analiza aktivnosti mrkog medvjeda (*Ursus arctos* Linnaeus, 1758) u prirodi i zatočeništvu

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Hrvatska je dom mrkom medvjedu, najvećem europskom grabežljivcu. Naša netaknuta priroda omogućila je opstanak medvjeda u šumovitim planinskim područjima na Dinarskom gorju. Nepreglednost takvog tipa staništa otežava direktno promatranje ponašanja i aktivnosti medvjeda. Ogrlice sa globalnim pozicijskim sustavom (GPS ogrlice) su općepoznata metoda za sakupljanje informacija o kretanju i lokacijama životinja. Na takve ogrlice moguće je postaviti senzore aktivnosti, te se u Hrvatskoj koriste već godinama i pridonose boljem razumijevanju dnevne i godišnje aktivnosti medvjeda. Podaci dobiveni preko senzora aktivnosti mogu se koristiti i za analizu određenih tipova ponašanja i aktivnosti individualnih jedinki. Podaci senzora aktivnosti dolaze u obliku niza brojeva te iz samih podataka nije moguće odrediti tip ponašanja. U ovom radu usporedila sam direktno zapaženo ponašanje medvjeda u zatočeništvu kojemu je stavljena GPS ogrlica sa brojčanim podacima dobivenima iz senzora aktivnosti. Predstavila sam tri modela aktivnosti koji razdvajaju tri tipa ponašanja (pasivno, niska aktivnost, srednja aktivnost) u odvojene brojčane raspone i primijenila ih na podatke o aktivnosti medvjeda na slobodi. Rezultati nisu bili povoljni, te bi daljnja istraživanja trebala uključivati GPS lokacije za razvijanje boljih modela aktivnosti.

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Analyses of Brown Bear (*Ursus arctos* Linnaeus, 1758) Activity in Natural Conditions and Captivity

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Croatia is a home to the Europe's largest carnivore, the brown bear. Its intact nature allows the brown bear to make use of the forested mountainous areas within the Dinara Mountain Range. However, the habitat inaccessibility makes it hard to directly observe bear behaviour and activity patterns. Global positioning system (GPS) collars are widely used as method to gain information of animal movements and locations. They can be fitted with activity sensors, and they have been used in Croatia for many years contributing to better understanding of daily and seasonal bear activity. The activity sensor data can also be used to analyse certain behaviour types and activity patterns of individual animals. The activity sensor produces a range of numeric data not accompanied by an explanation for activity types. To overcome this shortcoming, I used direct observations of a captive bear fitted with the collar containing the activity sensor to compare activity sensor numerical values and animal behaviour. Here I presented three activity models that separated three types of behaviours (passive, low activity, medium activity) into respective activity value ranges, and applied them to non-captive bear activity data. Results were inconclusive, and I suggested further analyses to include GPS locations for development of better activity models.

(34 pages, 18 figures, 5 tables, 36 references, original in: English)

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Key words: brown bear, animal behaviour, activity sensor, GPS collar, conservation.

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1. INTRODUCTION

The brown bear (*Ursus arctos* Linnaeus, 1758) is a large terrestrial mammal in the family Ursuidae, genus *Ursus*. Females weight between 100-200 kg, while males are considerably larger at 140-320 kg. As its name suggests, its fur is brown in colour, but it ranges from a lighter shade to almost black (figure 1). Its fur is double-coated, with a dense undercoat of short hair, and longer topcoat (Swenson et al. 2000). Despite being a carnivore, complete with large canines for killing and dismembering prey, their diet is mostly plant-based. They feed on green vegetation in spring, fleshy fruits during summer, then switch to berries and nuts when autumn comes (Naves et al. 2006). Mating season lasts from mid-May to early-July, when females will mate with multiple males. Gestation period is 6-8 weeks, and females give birth in January or February to 1-4 cubs. Cubs are helpless and dependant on their mother until age of 1.4 or 2.4 years. Bears start hibernation in late autumn and retreat to their dens for 3-7 months. In southern countries, bears are known to stay active through the year due to food availability during winters (Swenson et al. 2000).

Figure 1. A young male (left) and female (right) from bear sanctuary Kuterevo in Croatia.

The brown bear is one of the most widely distributed bear species, with populations in North America, Europe, and Asia (Waits et al. 1999). One of its subspecies, the Atlas bear (*Ursus arctos crowtheri* Schinz, 1844), existed even in North Africa, but has since gone extinct (Calvignac et al. 2008). According to the IUCN red list of threatened species, the total number of brown bears is estimated to be over 200,000 (McLellan et al. 2017). Globally, IUCN lists the brown bear as Least Concern (LC) and its population is considered stable. Regardless, most of the subpopulations are small and isolated, and as such require continuous conservation measures (Kaczensky et al. 2013).

1.1. Brown Bear in Europe and Croatia

Due to extensive hunting for centuries (Sørensen 1990), fragmentation, habitat destruction, and increasing human disturbances, the brown bear populations are highly fragmented in Southern, Central, and Western Europe (Swenson et al. 2000). The brown bear is found in 22 European countries (table 1), and can be classified into 10 isolated populations: Scandinavian, Karelian, Baltic, Carpathian, Dinaric-Pindus, Eastern Balkan, Alpine, Abruzzo, Cantabrian, and Pyrenean (Chapron et al. 2014).

Table 1. Brown bear populations in Europe according to Chapron et al. (2014) and the IUCN Red List Criteria

Population	Countries	Population size	Population area (km^2)	Population trend	Red List Category	Red List Criteria
Alpine	Italy, Switzerland, Austria, Slovenia	45 - 50	12,2000	stable to increasing	CR	D
Central Apennine	Italy	37 - 52	6,400	stable	CR	D
Eastern Balkans	Bulgaria, Greece, Serbia	600	39,000	stable	VU	D1
Baltic	Estonia, Latvia	710	50,400	increasing	LC	-

Cantabrian	Spain	196 - 210	7,700	stable to increasing	EN	D
Carpathian	Poland, Romania, Serbia, Slovakia, Ukraine	7,200	122,600	stable	LC	-
Dinaric-Pindus	Albania, Bosnia and Herzegovina, Croatia, Greece, Kosovo, Macedonia, Montenegro, Serbia, Slovenia	3,070	114,100	stable to declining	VU	C2a(i)
Karelian	Finland, Norway	1,700	381,500	stable	LC	-
Pyrenean	France, Spain, Andorra	22 - 27	17,200	stable	CR	D
Scandinavian	Sweden, Norway	3,400	466,700	increasing	LC	-

The Croatian brown bear subpopulation inhabits heavily forested mountainous areas within the Dinara Mountain Range (Kaczensky et al 2006). Elevations in the habitat range from sea level to 1,831 m, snow cover lasts for 60-165 days, and the forested areas are a mixture of multiple tree species, dominant of which are beech (*Fagus sylvatic* Linnaeus), fir (*Abies alba* Miller), and spruce (*Picea abies* Karst). The forest composition depends on elevation and exposure (Huber et al. 2008). The biological and ecological importance of this region is marked by the presence of two other endangered large European carnivores: the wolf (*Canis lupus* Linnaeus, 1758) and the lynx (*Lynx lynx* Linnaeus, 1758). Latter of them had to be reintroduced to the region because of extinction in 1911 due to over-hunting (Dečak et al. 2005, Sindičić et al. 2009). Unlike the lynx, the brown bear thrives in Croatia, and its current population is considered stable, at an estimated size of 1,000 individuals which meets the total habitat capacity (Kaczensky et al. 2013). The distribution range is presented in figure 2. It is a part of the Dinaric-Pindus population that spreads over nine countries; Albania, Bosnia and Herzegovina, Croatia, Greece, Kosovo, Macedonia, Montenegro, Serbia, and Slovenia (Chapron et al. 2014). However, just like with other subpopulations of the brown bear, there are continuous risks due to habitat fragmentation and human-related disturbances (Zedrosser et al. 2001).

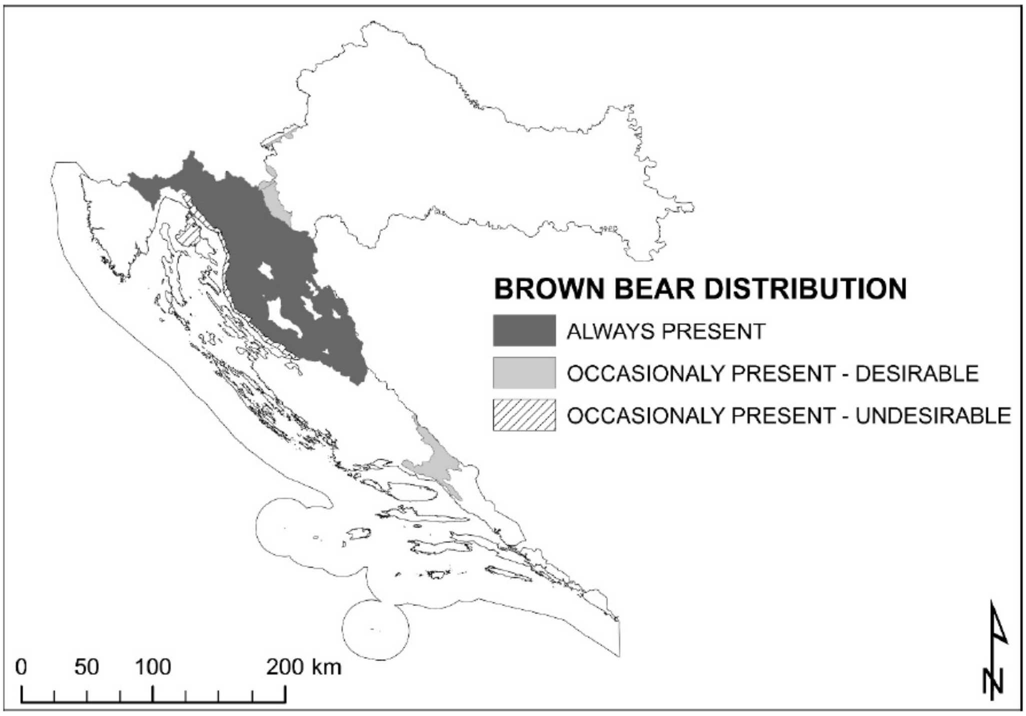

Figure 2. Brown bear range in Croatia, taken from Huber et al (2009).

1.2. Conservation Efforts

Historically, the brown bear was present throughout Europe, but it disappeared from most of the area due to ever-growing human presence and development. The combination of extermination by hunting and habitat destruction resulted in disappearance of the brown bear in most of Western Europe (Zedrosser et al. 2001), and its current distribution is presented in figure 3.

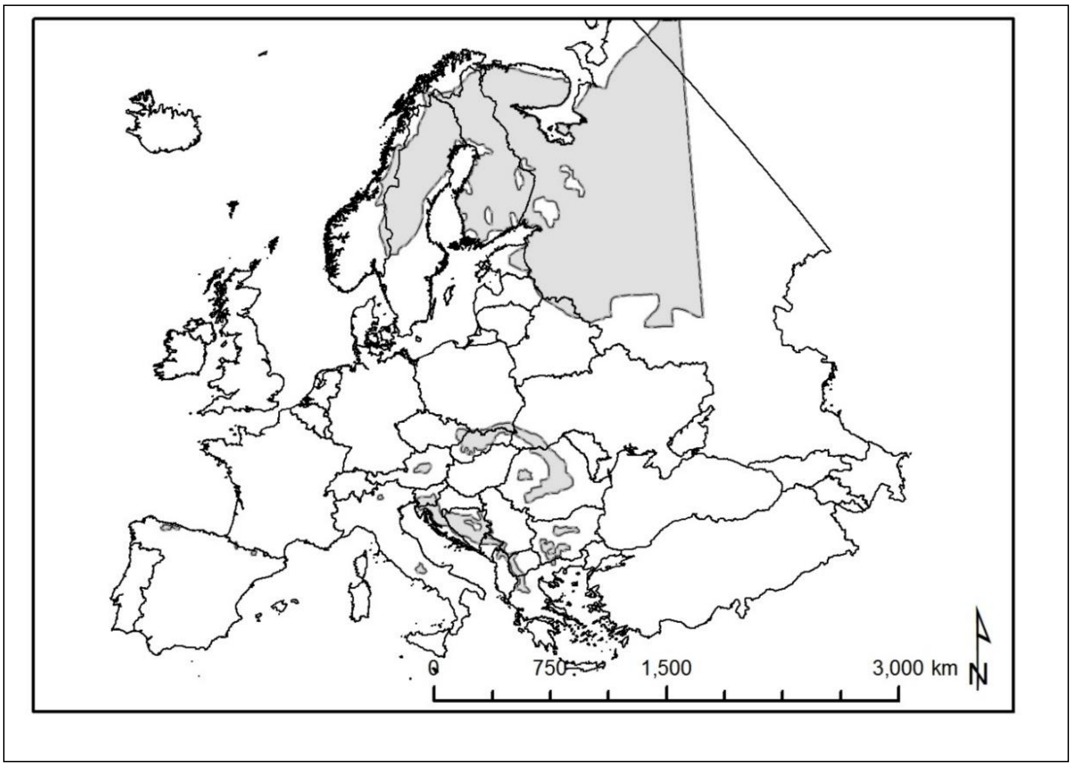

Figure 3. Brown bear distribution in Europe, taken from Kaczensky et al. (2013).

The brown bear is a protected species in accordance to Croatian Protected Species law (NN 2013). Conservation of brown bears is highly dependent on managing their interactions with local people, human activities, and international cooperation (Swenson et al. 2000). The latter is especially important for European subpopulations as most of them are shared among more than 2 countries (McLellan et al. 2016).

As for Croatia, the management of brown bear started in 1947 with the introduction of the first Hunting Act, followed by the listing of brown bear as a game species (Huber et al. 2008). Croatia has been under the contract of the Bern Convention ratified in 2000, which requires all European countries to maintain their wildlife and habitats in accordance to Appendices to the convention. The brown bear in particular is listed as a strictly protected fauna species, which means any deliberate killing, capture, keeping in captivity, disturbances and habitat destruction is prohibited. However, the Croatian subpopulation is considered stable and not critically endangered, so it was agreed (in accordance to Article 9 of the convention) that the status of the brown bear is that of a game species (Dečak et al. 2005). Conflicts with humans are in the present considerably low and it seems that the general acceptance of bears is positive, which is mostly due to income provided through hunting and tourism (Huber et al. 2008). Hunters help maintain the bear population as legal hunting is a source of income for them, however here we also face certain issues, such as possible overpopulating of bears, which might result in larger density of individuals in a habitat that may not have the necessary capacity, and could result in more frequent encounters with humans, or increased foraging at garbage disposal sites. Any conservation effort must consider these issues and, in case the legal bear status ever changes from game species to endangered, possible retaliation of hunters and others who will have lost their economic benefits due to a hunting ban. In order to maintain a stable bear population, constructing a management plan is important. The brown bear management plan for Croatia was approved in 2004, and amongst other things it includes monitoring the bear population through collection of data on mortality, reproduction, and bear presences through use of genetic methods (Huber et al. 2008). The plan also priorities habitat conservation, which has been achieved by building green bridges at important crossing places for wildlife (Kusak et al. 2009). Another important issue the management plan had to address was a food source situation. Bears will often forage through garbage disposals sites looking for food and such sites must be made inaccessible to bears for safety of bears and humans likewise (Huber et al. 1998).

1.3. Monitoring

One way to keep track of bears, their feeding areas, denning sites, habitat range, etc. (all of which are important for conservation of both the animal and its habitat), is by using tracking collars. This is a well-known practice and VHF and GPS collars have been used to track animal movement for a long while. They can be useful in determining where to build green bridges or animal crossing areas across highways (Kusak et al. 2009), to investigating habitat ranges and habitat use (Bourgoin et al. 2009; Theuerkauf & Jedrzejewski 2002; Saltz 1994). While GPS collars on their own can be used to record distances covered by an animal (Ganskopp & Johnson 2007), we can also separate active and inactive behaviours using activity sensors fitted on the tracking collar (Coulombe et al. 2006; Gottardi et al. 2010). Since behaviour is a response to the environment and it is a great indicator of the animal's well-being, identifying different behaviour patterns is of significant importance for studying any species and managing possible conservation efforts (Shepard et al. 2008). It is also important in understanding the habitat use and responses to disturbances (Löttker et al. 2009). While animal behaviour is usually researched through direct observation, it is often not possible to find an animal in the wilderness or get close enough to determine its behaviour. This is especially true for elusive and wide-ranging species, and in such cases using activity sensors to determine behaviour can be of great benefit (Moen et al. 1996; Adrados et al. 2003; Bourgoin et al. 2008). Those types of study have already been conducted on various species. A study on mouflon successfully used motion sensors on a GPS collar to determine seasonal variations in activity patterns (Bourgoin et al. 2008). Adrados et al. (2003) used the GPS collar activity sensor to separate active from inactive behaviours of wild red deer (*Cervus elaphus* Linnaeus, 1785) where they compared data from observation of tame deer with data obtained from activity sensors from collars fitted on wild deer. They defined active behaviour as feeding or moving, and inactive as standing, grooming or sleeping. Their results showed a correspondence between activity sensor data and observed activity data. Moen et al. (1996) used direct observation and data from activity counters to interpret moose (*Alces alces* Linnaeus, 1785) behaviour, and conducted that activity counts could be used to study seasonal changes in moose activity. However, they also pointed out that activity sensors may be susceptible to failure during cold weather. Other studies tested accuracies of various GPS collars to predict behaviours; such as a test in prediction of European roe deer (*Capreolus capreolus* Linnaeus, 1785) behaviours, categorized as active (feeding, moving) and inactive (bedded, standing). Results showed that activity data and movement data can be used to distinguish between two types of active behaviours where one includes movement and the other does not (Gottardi et al. 2010). They explain that active behaviour without movement may correspond to deer feeding in small areas.

The activity patterns of bears have also been studied by radio telemetry using VHF collars, Kaczensky et al. (2006) investigated effect of disturbances on brown bears in Slovenia and Croatia using radio-collars to determine increased nocturnal activity of adults, which they assumed was a result of negative experiences with humans. Though this study didn't use activity sensors, other studies on bears had success in determining different levels of activity in a similar way as previously mentioned studies on grazers. A study on Japanese black bears (*Ursus thibetanus japonicus* Schlegel, 1857) successfully used activity sensors fitted to two different types of GPS collars (GPS3300S and GPS4400S, Lotek Wireless Inc., Canada) to determine activity patterns of captive black bears due to shortage of behaviour data for wild bears. They were unable to compare specific behaviours with activity data and examined only entirely active or entirely inactive behaviours (Kozakai et al. 2008). Finally, a study on brown bears (Gervasi et al. 2006) tested an activity sensor mounted on GPS-GSM collars using data from captive and wild individuals. They made a point that individual behaviour, collar tightness, neck size should be taken into consideration when studying activity patterns of wild animals using activity sensors. They also encountered higher activity values for bears that were eating, grooming, or grazing, despite these behaviours requiring less energy than walking.

1.4. The Goal

The goal of this project was to investigate whether the numerical values that represent the activity levels obtained from the activity sensor mounted on a GPS tracking collar can give us insight into bear behaviour and activity patterns in the wilderness by using data gained through direct observation of a captive bear fitted with the activity sensor. It has already been shown that activity patterns of an animal can provide an insight in its behaviour, behavioural changes due to human disturbances or natural causes such as changing of the seasons (Adrados et al. 2003). And it could even provide information about usage of denning or feeding sites without direct observation (Gervasi et al. 2006). Determining animal activity patterns in certain areas could alert us of potential conservation importance of those areas (Adrados et al. 2003). While green bridges in Croatia currently do a good job at connecting the bears' territories in that the fragmentation of the habitat has lesser effect on the bear population than is the case in other parts of Europe (Huber et al. 2008; Swenson et al. 2000; Kusak et al. 2009), keeping track of our bears should remain a priority for both their benefit and the benefit of people who live in areas that are frequented by bears. Combined with GPS tracking of covered distances and animal movement, determining behavioural and activity patterns could give us a valuable insight useful for future conservation efforts and management plans.

2. MATERIALS AND METHODS

Activity data was collected using a Vectronic GPS tracking collar (model GPS Plus) with a built-in activity sensor. The activity sensor is a dual-axis motion sensor that records horizontal (side to side) and vertical (up and down) movements of the animal's head and neck (i.e., collar acceleration) as numerical values ranging from 0 to 255 for each direction (Kozakai et al. 2008). These values are averaged within 5-minute time intervals and are a result of both the intensity and duration of movements (Gervasi et al. 2006). For this study, one captive 4-year old male brown bear was fitted with the collar. The bear was kept in an enclosure at Bear Sanctuary Kuterevo, in village Kuterevo, Lika-Senj County, Croatia, along with two other bears of similar age (figure 4). Due to financial and time limitations, as well as health risks that come with putting large animals under anesthesia, we were unable to fit more than one bear with a collar. Since one of the goals of this project was to use the results to analyse activity and behaviour of bears in wilderness, I also used activity data from a wild bear captured on 15.5.2015. at location "Tisova kosa", Vrbovsko. The GPS collar was fitted on an adult male bear of a mass of 186 kg. The collar was the same as the one used on the captive bear, and it had the same activity sensor that recorded data over the period of 541 days (20.5.2015. – 11.11.2016.).

Figure 4. A part of the enclosure at bear sanctuary Kuterevo where this study was conducted.

The captive bear was observed, and video recorded over the period of five consecutive days (12.11.2016. - 16.11.2016.). Since it was important to capture multiple behaviours of the bear that could be compared to data from the activity sensor, I was recording whenever the bear was most active (during feeding times, walking, etc.) which resulted in 30 minutes to 1-hour long sequences that were recorded throughout the day. The recordings were processed using Wondershare Video Converter and VirtualDub software. After discarding invalid recordings, the total amount of video data was 725 minutes. To determine durations of different behaviour types which I wanted to use in activity analysis, I used Solomon Coder, a free program for analysing videos. This program allowed me to differentiate between three main behaviours used in further analysis: walking, feeding, and passive behaviour. Passive behaviour consisted of different behaviours (standing, sitting, resting, sleeping), but they were clustered together because this group of behaviours all resulted in extremely low activity levels (data from the activity sensor) and it wasn't possible to differentiate between different passive behaviours in later analysis.

Furthermore, except for passive behaviour which was present in abundance, I didn't have recordings of feeding and walking that respectively lasted for 5 minutes or longer. Because the activity sensor averages the data received within 5-minute time periods, this was a difficulty as it meant I didn't have clear periods of one behaviour type which I could then assign to a certain activity level through analysis, but rather a mixture of multiple active and passive behaviours within one 5-minute period. To overcome this issue, I decided to split the behaviours to active and passive. This was done in accordance to other studies done on bears and deer (Gervasi et al. 2006; Kozakai et al. 2008; Gottardi et al. 2010). A time interval was classified as passive if the bear spent more than 50% of total time standing still, sitting, resting or sleeping. And it was classified as active if the bear spent more than 50% of total time walking or feeding.

I also attempted to distinguish between finer levels of activity and see if it was possible to differentiate between walking and feeding using data from the activity sensor. Due to a very low amount of data for active behaviours, this wasn't easy to achieve so I decided to create different models. As it will be shown in the results, the passive classification proved correct for all of them, so I continued using the same classification (a time interval is classified as passive if >50% of total time consists of passive behaviours). The differences between models were in low and medium activity classifications; First model (Model 1 in results) classified a time interval as low activity if more than 50% of total time consisted of feeding, and as medium activity if more than 50% of total time consisted of walking. The second model (Model 2 in results) classified a time interval as medium activity if more than 70% of total time consisted of walking, otherwise it was classified as low activity. I used these models to define a separation point in activity sensor data that marks the border between different behaviour types, however due to a small amount of higher-activity data and overlapping it wasn't possible to define ranges with purely one type of behaviour so I assigned separation points to each model based on highest percentage of desired behaviour type within that value range.

Separation points for different activity models mentioned above were selected using Microsoft Excel. Correlation between collar data and direct observation (separated to individual behaviours) was tested using graphical analyses in Microsoft Excel and statistical analyses in open source programming language R. I used Spearman's Correlation Test to analyse correlation between individual behaviours and activity levels for captive bear data, and I used Mann-Whitney U Test to test the difference in distribution of data from activity sensors for different activity models, between passive and active behaviours. Due to lack of visual data of behaviour and movement for the wild bear, I was unable to test for any kind of correlation between its real-time activity and data received from the activity sensor. However, the most suitable activity model was used for application on the dataset from the wild bear.

3. RESULTS

I found that the percentage of recorded active behaviours was much smaller than passive behaviours (table 2.).

Table 2. Total number of active and passive time intervals in the sample (N = 144).

Active	Passive
47	97

I tested the correlation between collar data and direct observation of the captive bear for each individual behaviour to make sure recorded behaviours corresponded with activity sensor data. Feeding (with or without movement), and walking. Correlation between passive behaviour (sleeping, resting, standing, sitting) and activity data was statistically significant (X-act: $p < 0.001$, $r = -0.86$; Y-act: $p < 0.001$, $r = -0.79$; X+Y: $p < 0.001$, $r = -0.83$, $N = 144$, Spearman correlation test), and durations of recorded passive behaviour decreased as activity levels increased (figure 5).

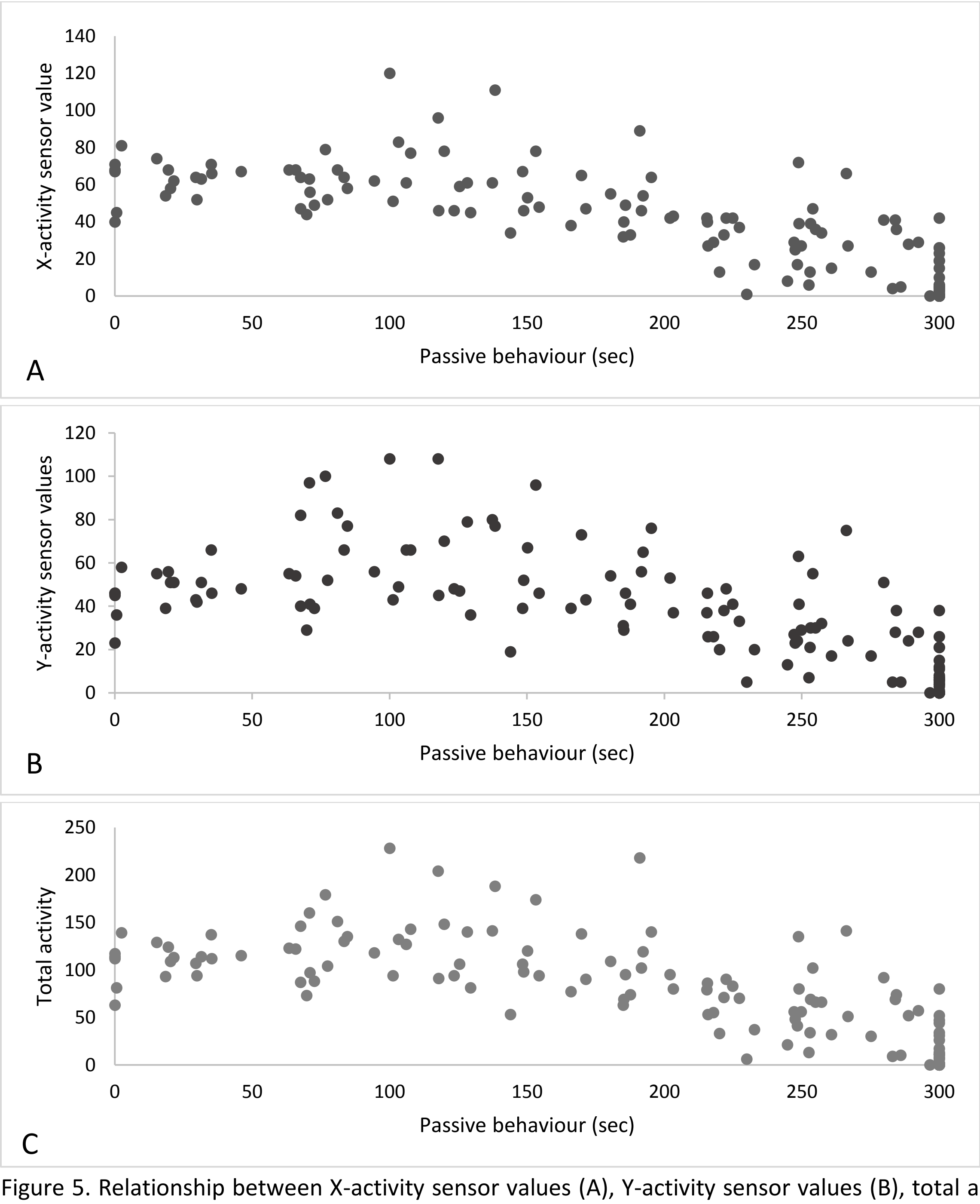

Figure 5. Relationship between X-activity sensor values (A), Y-activity sensor values (B), total activity (C), and duration of observed passive behaviour (sleeping, resting, standing, sitting).

Correlation between feeding (with or without movement), which was classified as active behaviour, and activity data was statistically significant (X-act: $p < 0.001$, $r = 0.70$; Y-act: $p < 0.001$, $r = 0.56$; X+Y: $p < 0.001$, $r = 0.64$, $N = 144$, Spearman correlation test). However, the increase in duration of "feeding" was not clearly visible, and there were quite a few higher values present for shorter durations of feeding intervals, especially for vertical movement or Y-activity. This was probably due to feeding being associated with longer periods of either standing still or walking (figure 6).

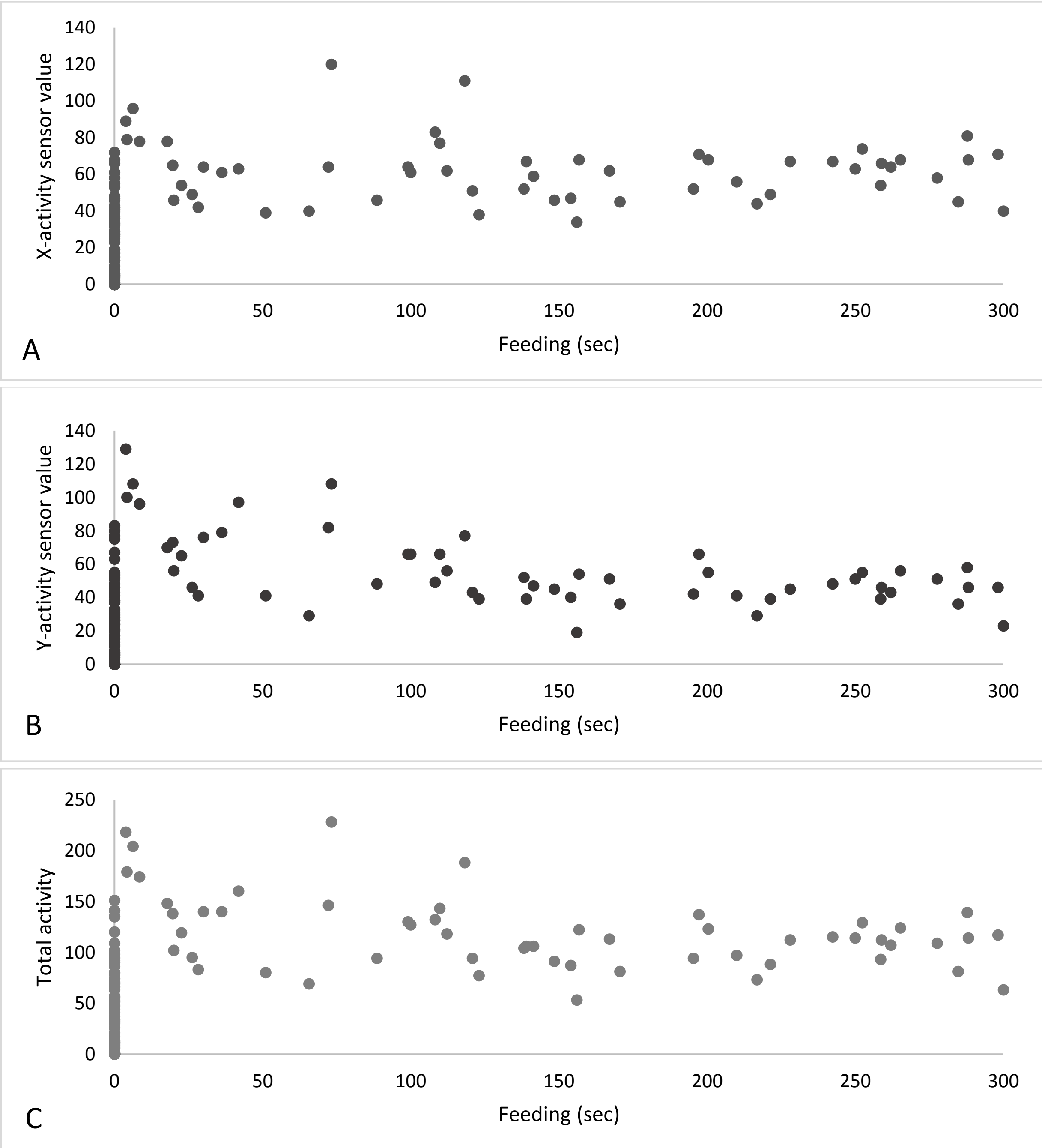

Figure 6. Relationship between X-activity sensor values (A), Y-activity sensor values (B), total activity (C), and duration of observed active behaviour (feeding with or without movement).

Correlation between the second active behaviour - walking, and activity data was also statistically significant (X-act: $p < 0.001$, $r = 0.68$; Y-act: $p < 0.001$, $r = 0.79$; X+Y: $p < 0.001$, $r = 0.74$, $N = 144$, Spearman correlation test). We can see from figure 7 that 5-min time intervals consisting solely of walking were not observed.

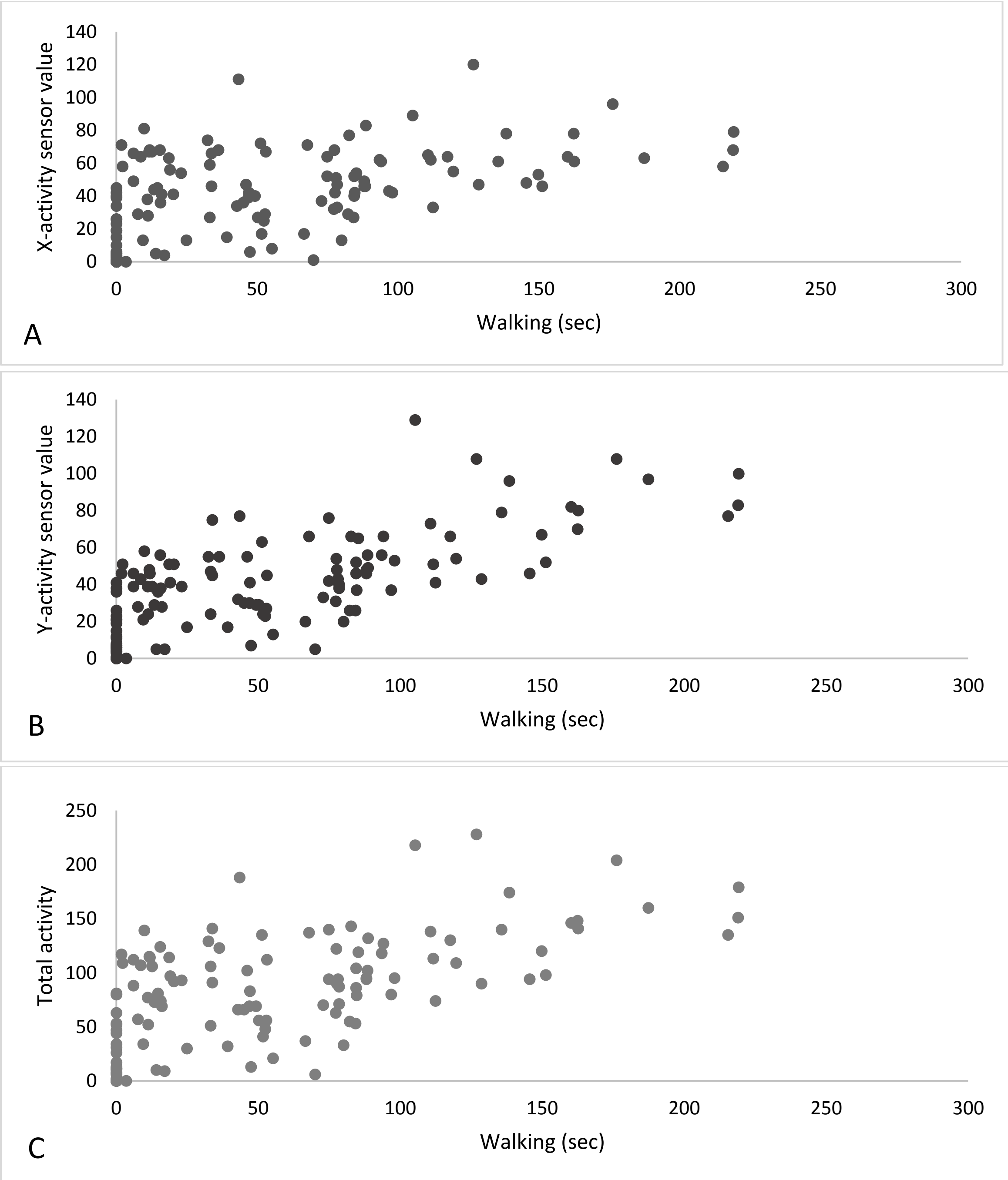

Figure 7. Relationship between X-activity sensor values (A), Y-activity sensor values (middle), total activity (B), and duration of observed active behaviour (C).

3.1. Passive – Active Model

I analysed activity data of horizontal (X-activity) and vertical (Y-activity) movements separately, as well as total activity data. Total activity is simply the overall acceleration in both directions; $X + Y$. Following that, the range of total activity is 0-510 since the range of vertical and horizontal direction is 0-255 respectively. The reason why I conducted all three analyses was to see which type of acceleration, if any, was best to use in predicting activity patterns of bears. It is also worth mentioning that I excluded any values higher than 120 because I had only one value in that range. Statistical and graphical analyses (figure 8) showed that there was a significant difference in activity level values for horizontal movement (side to side) for passive and active behaviours ($W = 317.5$, $p < 0.001$, Mann-Whitney U Test, $N = 144$).

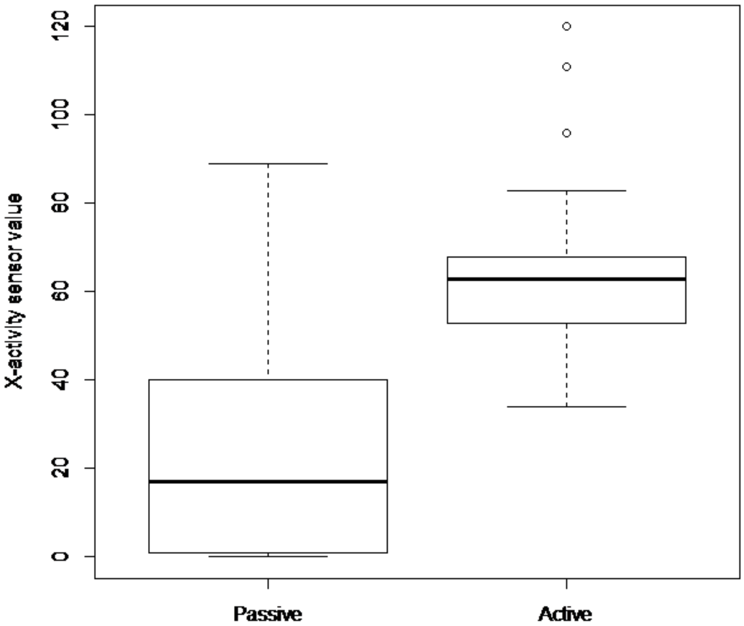

Figure 8. Distribution of X-activity levels (activity sensor value) for “passive” and “active” time intervals (passive: >50% of time spent of resting, standing or sitting; active: >50% of time spent walking or feeding). Outliers are marked as open circles, the box is the median, 25% and 75% quartiles, and whiskers show upper and lower extremes.

For vertical movement (up and down), results are similar (figure 9) and there was a significant difference in activity values for passive and active behaviours ($W = 599.5$, $p < 0.001$, Mann-Whitney U Test, $N = 144$). It seems that there were some outliers present for both horizontal and vertical movement, meaning that what was classified as passive (or active) behaviour through direct observation was assigned to an exceptionally higher (or lower) activity count from the activity sensor. Outliers were excluded from further analyses.

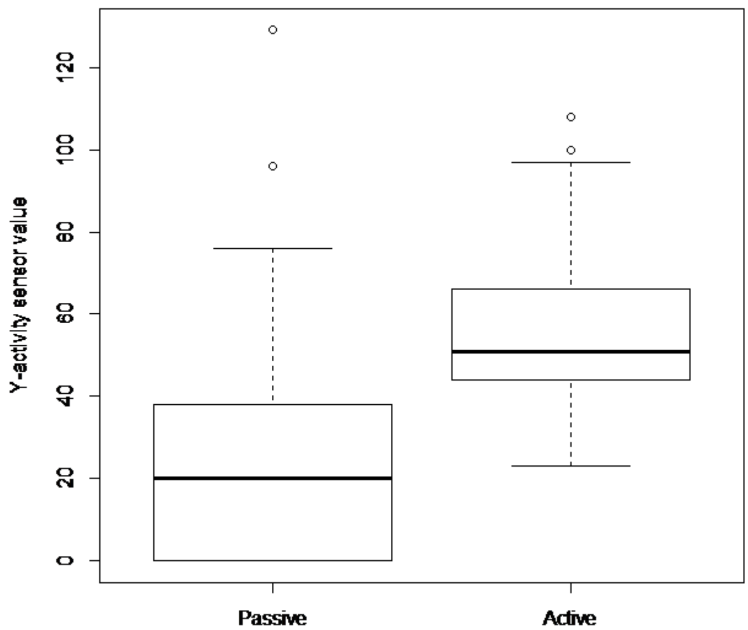

Figure 9. Distribution of Y-activity levels (activity sensor value) for “passive” and “active” time intervals (passive: >50% of time spent of resting, standing or sitting; active: >50% of time spent walking or feeding). Outliers are marked as open circles, the box is the median, 25% and 75% quartiles, and whiskers show upper and lower extremes.

Finally, a distribution of total activity levels (the sum of “X acceleration” and “Y acceleration”) was again significantly different for passive and active time intervals respectively ($p < 0.001$, Mann-Whitney U Test, N = 144) as shown in figure 10.

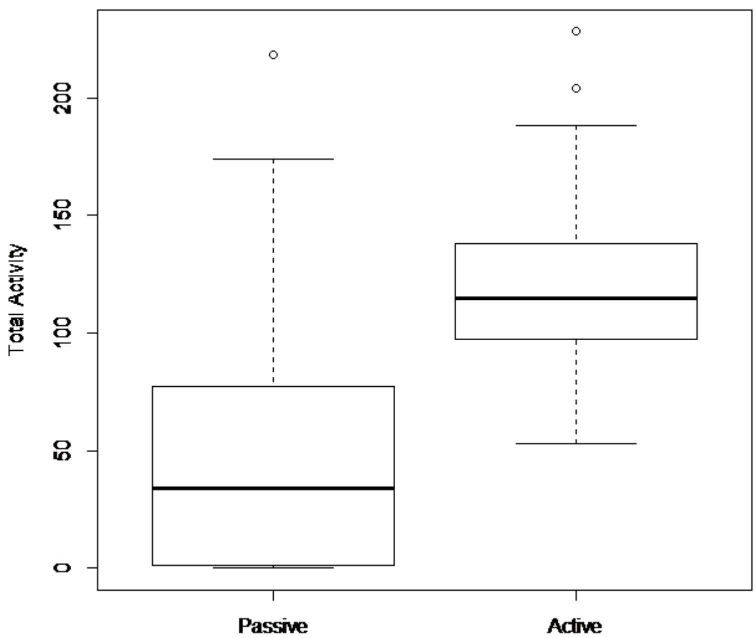

Figure 10. Distribution of total activity levels (X+Y) for “passive” and “active” time intervals (passive: >50% of time spent of resting, standing or sitting; active: >50% of time spent walking or feeding).

By comparing the activity data with data from direct observation, I decided on the separation point between passive and active behaviour type separately for horizontal, vertical, and total acceleration (activity level) based on percentage of active and passive counts in each category. Results are shown in table 3. As it could be expected due to a low count of active behaviour samples, it was not possible to get a higher than 70% of active counts per any activity level range, but it was still possible to distinguish between count ranges with mostly passive behaviour, and count ranges with mostly active behaviour.

Table 3. Percentage of two activity types in the captive bear per each orthogonal direction and total activity, outliers were excluded.

Time interval classification	**Activity level (X)**		**Activity level (Y)**		**Total activity (X+Y)**	
	0 - 45	*46 - 120*	*0 - 45*	*46 - 120*	*0 – 100*	*101 - 240*
Active (%)	2.6	***72.2***	14.9	***67.4***	13.1	***76.2***
Passive (%)	***97.4***	27.8	***85.1***	32.6	***86.9***	23.8
N of samples	87	54	94	46	99	42

3.2. Passive – Low Activity – Medium Activity Models

Most of the studies investigating behaviour prediction through indirect methods using activity sensors were not able to separate the behaviours to anything more specific than “passive” or “active”. Here I tried to group levels of activity to three different categories: “passive”, “low activity”, and “medium activity”. The idea was that “medium activity” should consist more of walking than feeding or foraging, while it was the opposite for “low activity” range. Again, the data was analysed for both orthogonal directions, as well as total activity.

3.2.1. Activity Model 1

Distribution of X-activity levels from activity sensor for passive (P) and low activity (LA) versus passive and medium activity (MA) behaviours was significantly different (P-LA: $p < 0.01$, N = 134; P-MA: $p < 0.01$, N = 108, Mann-Whitney U Test). However, the difference in activity levels for low and medium activity was not significant ($p = 0.2$, N = 46, Mann-Whitney U Test) and it appeared there was too much of an overlap between activity levels for finer separation to low and medium activity (figure 11).

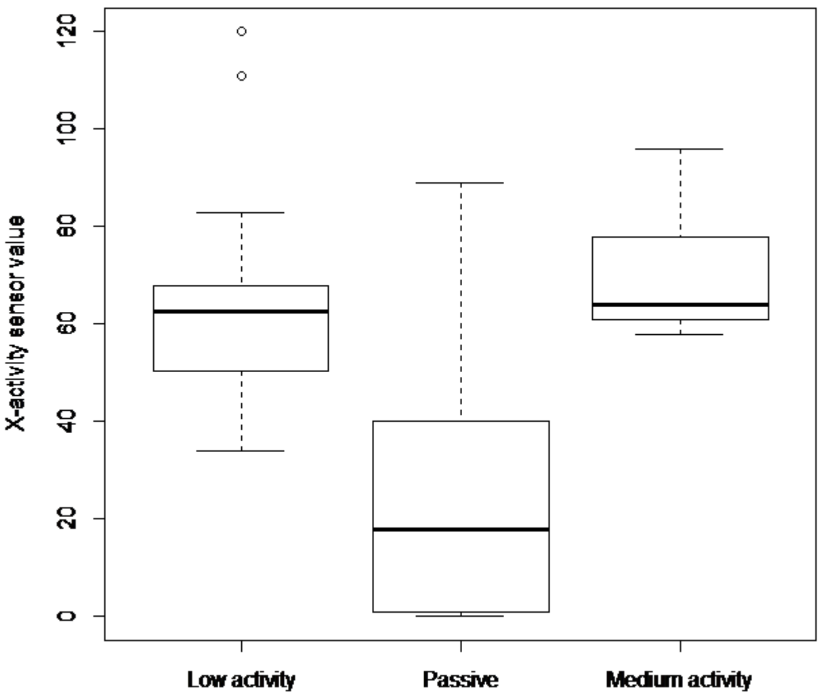

Figure 11. Distribution of X-activity levels (activity sensor value) for "passive", "low activity", and "medium activity" time intervals for activity model 1.

Y-activity values for this model were significantly different for passive and low activity, and passive and medium activity (P-LA: $p < 0.01$, N = 134; P-MA: $p < 0.01$, N = 108, Mann-Whitney U Test), but was interestingly also significant for low and medium activity ($p < 0.01$, N = 46, Mann-Whitney U Test) as can be seen in figure 12.

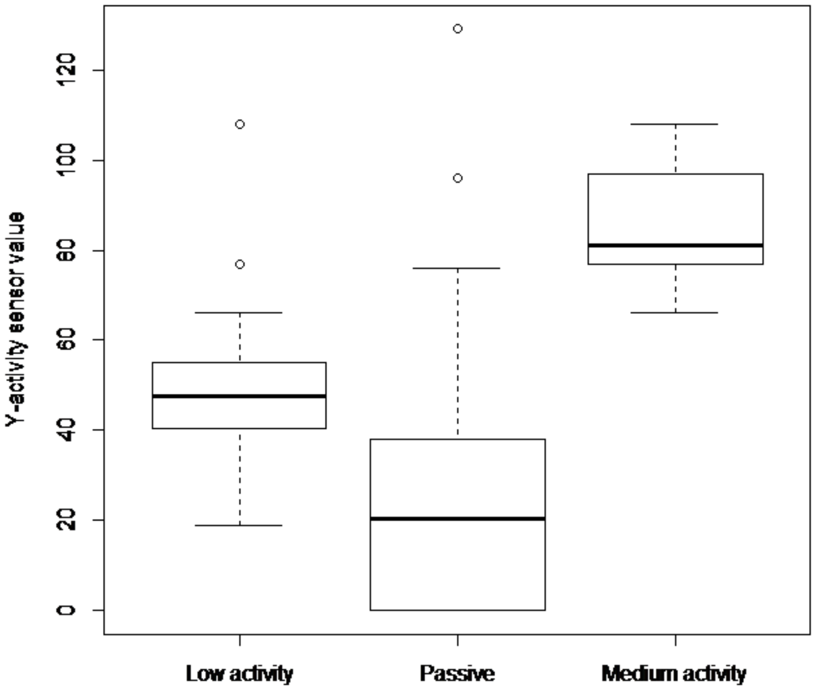

Figure 12. Distribution of Y-activity levels (activity sensor value) for "passive", "low activity", and "medium activity" time intervals for activity model 1.

Figure 13 shows similar results for total activity distribution, and again there was significant difference in distribution for all activity types (P-LA: $p < 0.01$, N = 134; P-MA: $p < 0.01$, N = 108; LA-MA: $p < 0.01$, N = 46, Mann-Whitney U Test).

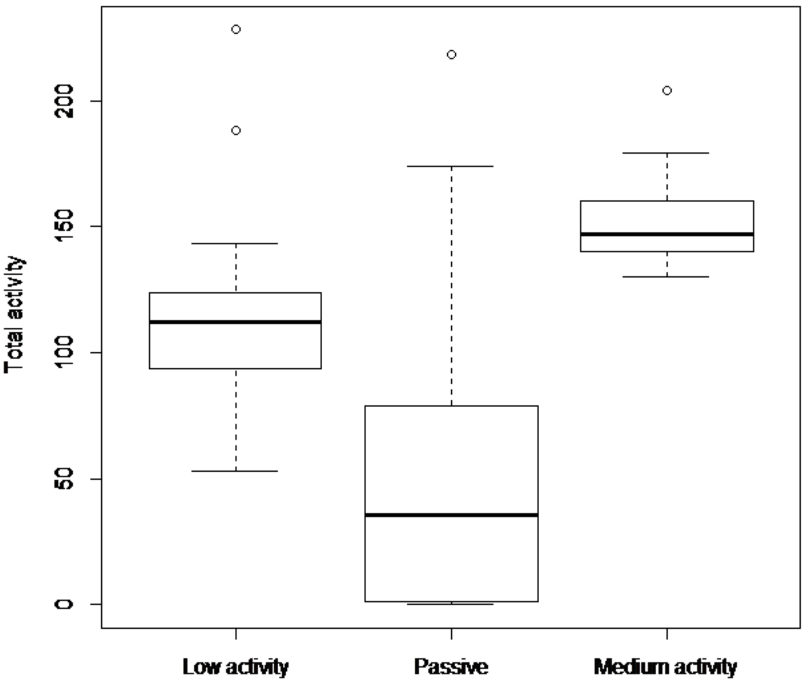

Figure 13. Distribution of total activity levels (X+Y) for "passive", "low activity", and "medium activity" time intervals for activity model 1.

Due to overlapping, a clear seperation point between behaviours was not visible. Consequently, like with previous models, I based the seperation on the percentages of each behaviour present within a specified range for each orthogonal direction, and total activity (table 4).

Table 4. Percentage of three activity types in the captive bear per each orthogonal direction and total activity, outliers were excluded.

Time interval classification	Activity level (X)			Activity level (Y)			Total activity (X+Y)		
	0 - 45	*46 - 69*	*70 - 120*	*0 - 45*	*46 - 69*	*70 - 120*	*0 – 100*	*101 - 139*	*140 - 240*
Med. activity (%)	0	16.3	***25***	0	3	***75***	0	3.3	***63.6***
Low activity (%)	5.7	***53.5***	50	14.9	***58.8***	0	12.1	***70***	9.1
Passive (%)	***94.3***	30.2	25	***85.1***	38.2	25	***87.9***	26.7	27.3
N of samples	87	43	12	94	34	12	99	30	11

3.2.2. Activity Model 2

Results for the second activity model for X-activity showed significant difference for distribution of activity levels for passive (P) and low activity (LA) behaviours, and between passive and medium activity (MA) behaviours (P-LA: $p < 0.01$, N = 136; P – MA: $p < 0.01$, N = 106, Mann-Whitney U Test), but there was no significant difference between low activity and medium activity ($p = 0.2$, N = 46, Mann-Whitney U Test). Figure 14 shows overlapping between LA and MA activity level distribution, similarly to previous model.

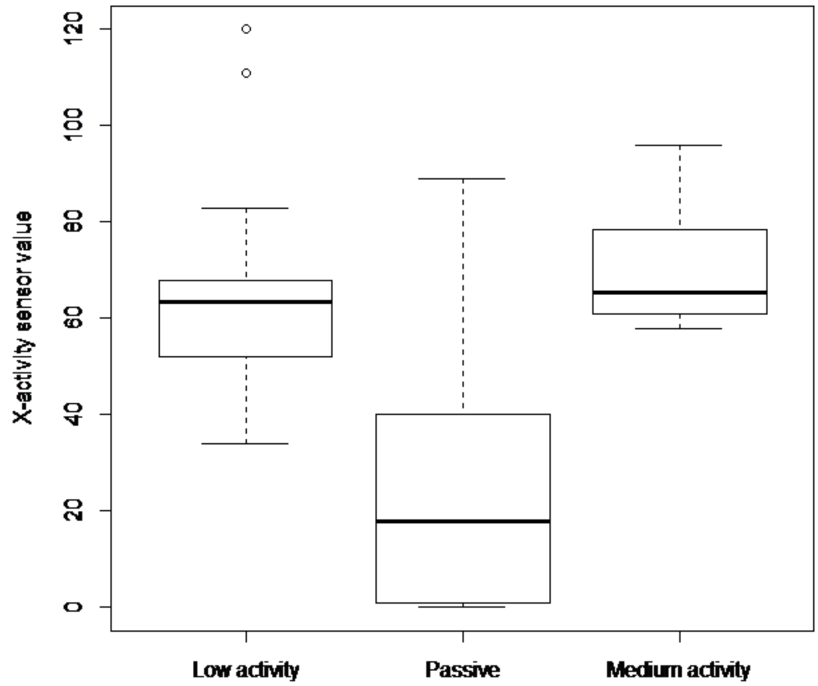

Figure 14. Distribution of X-activity levels (activity sensor value) for “passive”, “low activity”, and “medium activity” time intervals for activity model 2.

Distribution for Y-activity was significantly different comparing low activity and passive, medium activity and passive, then by comparing low and medium activity (P-LA: $p < 0.01$, N = 136; P – MA: $p < 0.01$, N = 106; LA – MA: $p < 0.01$, N = 46, Mann-Whitney U Test), again a repeat of the Model 1 results for Y-activity (figure 15).

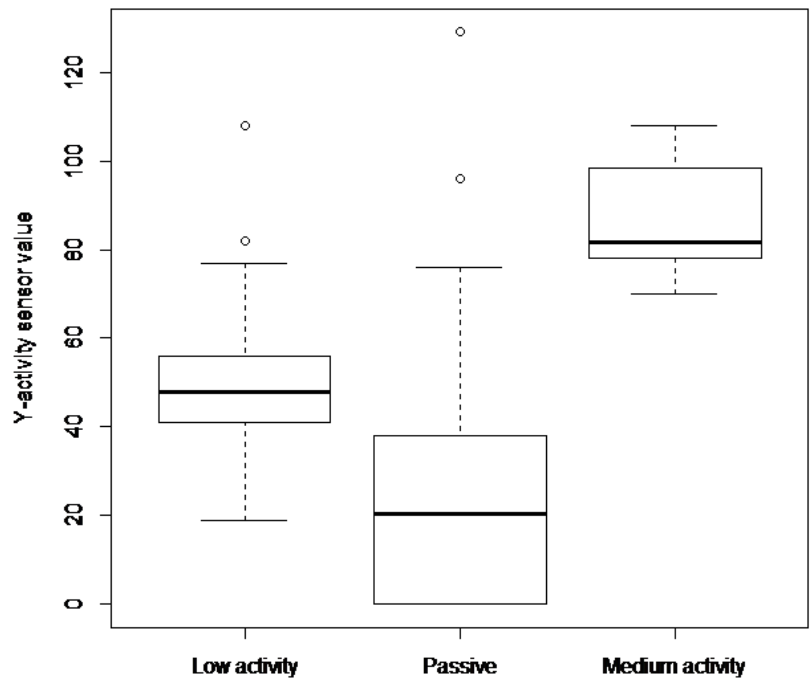

Figure 15. Distribution of Y-activity levels (activity sensor value) for “passive”, “low activity”, and “medium activity” time intervals for activity model 2.

Finally, distribution of total activity values across passive, low activity, and medium activity behaviour types was significantly different for passive and low activity, passive and medium activity, and low and medium activity ((P-LA: $p < 0.01$, N = 136; P – MA: $p < 0.01$, N = 106; LA – MA: $p < 0.01$, N = 46, Mann-Whitney U Test) as shown in figure 16.

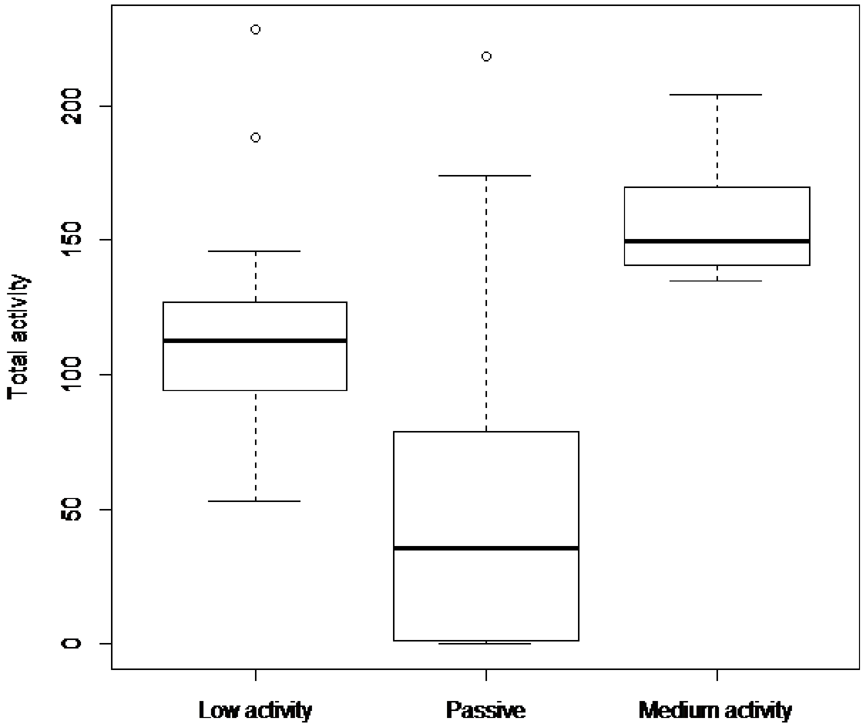

Figure 16. Distribution of total activity for “passive”, “low activity”, and “medium activity” time intervals for activity model 2.

Separation points were again based on percentages of specific behaviours. All three types of acceleration had a much lower percentage of “medium activity” behaviours in the highest range than it was expected, and a slightly higher percentage of low activity behaviours within the assigned range than model 1 (table 5).

Table 5. Percentage of three activity types in the captive bear per each orthogonal direction and total activity, outliers were excluded.

Time interval classification	Activity level (X)			Activity level (Y)			Total activity (X+Y)		
	0 - 45	*46 - 69*	*70 - 120*	*0 - 45*	*46 - 69*	*70 - 120*	*0 – 100*	*101 - 139*	*140 - 240*
Med. activity (%)	0	11.6	***25***	0	0	***66.7***	0	3.3	***58.3***
Low activity (%)	5.7	***58.1***	66.7	14.9	***61.8***	8.3	12.1	***73.3***	16.7
Passive (%)	***94.3***	30.2	8.3	***85.1***	38.2	25	***87.9***	23.3	25
N of samples	87	43	12	94	34	12	99	30	12

3.3. Application

Application of previously described activity models was done on activity sensor data of a non-captive bear. As the difference between X acceleration, Y acceleration, and total activity data for the non-captive bear was negligible, I deemed it unnecessary to present all three analyses, and I decided to use only total activity results. Another reason was because total activity had the most consistent results for captive bear data too. Categorization of "low activity" and "medium activity" behaviours was done on seasonal basis (figure 17) and monthly basis (figure 18). As I didn't have information about the bear's locations, movements, and covered range, I was unable to determine the accuracy of results gained through activity models.

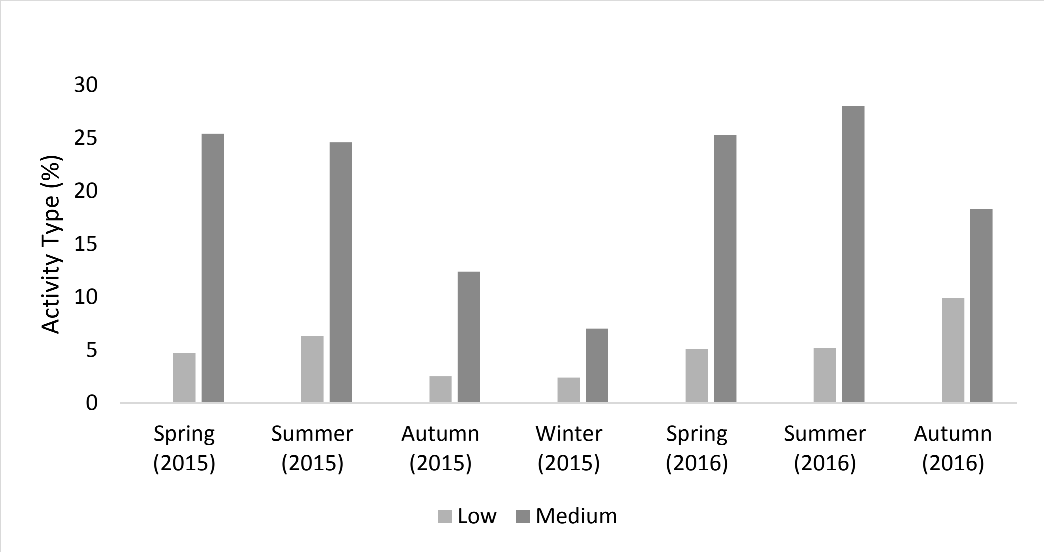

Figure 17. Percentages of “low activity” and “medium activity” seasonal data for non-captive bear for years 2015. and 2016.

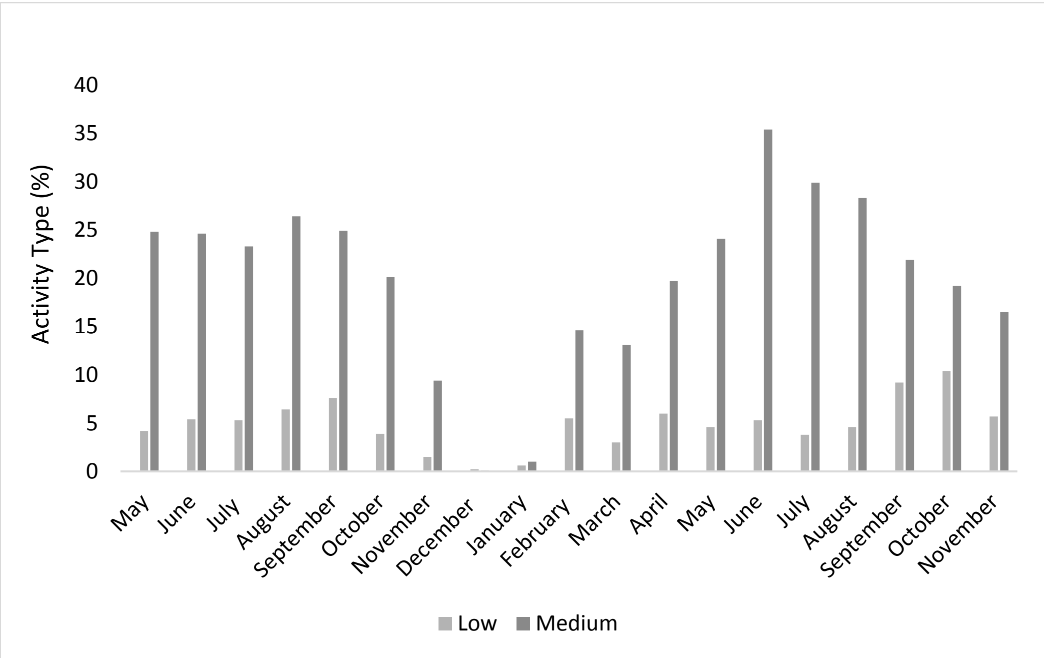

Figure 18. Percentages of “low activity” and “medium activity” data for non-captive bear per month for years 2015. and 2016.

4. DISCUSSION

Using the passive-active model described in this thesis, it was possible to separate between passive and active behaviours to a certain degree. Distribution of activity sensor values was significantly different between passive and active behaviours. Passive behaviour was presented with activity value range from 0 to 45 (data obtained from the activity sensor). It wasn't possible to separate the passive behaviour group to more basic behaviours such as resting, sitting or standing as there was no apparent difference in activity sensor values for those types of activity. Even though it wasn't presented in the thesis, sleeping continuously resulted in activity value 0, while resting, standing, and sitting had a range of activity values apparently dependent on frequency of neck or head movements. The activity value ranges from 46 - 120 assigned to active behaviours were less accurate. While the reason for lower accuracy was not known, it was possibly due to a low amount of active behaviour observations, which was less than half than that of passive behaviour.

In the design of this model, I didn't differentiate between walking and feeding (which were two active behaviours recorded during observation of the captive bear). The range in this model tells that the bear most likely spent more than 50% of its time within one 5-minute-long interval walking and/or feeding. Feeding was described as an active behaviour regardless if it was sedentary or non-sedentary. Gervasi et al. (2006) found that feeding behaviours resulted in higher activity sensor values despite being less intensive than walking, and indeed that is backed up by the fact that activity sensor will be affected by neck and head movements which is more pronounced in feeding behaviours (Gottardi et al. 2010). Figure 6 in "Results" section showed that feeding stayed at a relatively consistent activity sensor value range, which couldn't be said for passive behaviour nor walking. Duration of passive behaviour decreased with increment of activity sensor value as seen in figure 5, which was to be expected since decreased duration of passive behaviour meant increased duration of active behaviours such as walking. And indeed, figure 7 in "Results" sections showed a positive correlation between walking and activity sensor values. It is interesting that feeding stayed at relatively same level regardless of its duration. It should be noted that due to nature of the activity sensor on the tracking collar (activity counts are averaged every 5 minutes), I wasn't able to record a clear interval of 5 minutes consisting of a single active behaviour. So, the correlation between activity values and feeding could be attributed to the fact that it was often mixed with either passive behaviours such as standing or sitting, which could account for lower activity values for longer durations of feeding, but it also sometimes involved quite a bit of walking and foraging. This could account for higher activity values for shorter durations of feeding. In a few instances the bear was digging in search for food, a behaviour that could again increase the activity sensor value even though the bear spent most of that time in one spot.

Since a few studies regarding activity models in wild animals used total activity for their predictions instead of just horizontal or vertical movement, i.e. X or Y acceleration (Gervasi et al. 2006; Kozakai et al. 2008; Gottardi et al. 2010) based on the assumption that GPS collars make it hard to distinguish between resting, and foraging or grazing with slow pace movement due to GPS location errors (Schlecht et al. 2004; Ganskopp & Johnson, 2007), I decided to use the same method. However, studies that explained the benefit of usage of total activity over just X or just Y acceleration, also included GPS locations in their analysis (Ungar et al. 2005; Schwager et al. 2007). As I didn't have that type of data, I decided to include analysis for X and Y acceleration as well for comparability. From the results, there doesn't appear to be a significant difference between appointed activity value ranges for X acceleration and total activity. Except that favourable range for active behaviour was slightly higher for total activity (101 - 240) than for X acceleration (46 - 120). The acceleration on Y axis had the lowest count of active behaviours in the appointed range which could be because Y axis acceleration, i.e. vertical (up and down) movement of the head and neck is not as pronounced in walking, resulting in similar activity sensor values as for passive behaviour. Furthermore, the activity sensor value could also be influenced by the terrain type; whether the animal was moving on an even terrain, uphill or downhill, etc.

The second type of models included three activity or behaviour types; passive behaviour, "low activity" behaviour, and "medium activity" behaviour. Both active behaviour types were a mixture of smaller or larger percentages of feeding and walking while the passive behaviour retained the same classification as in the previous model as explained in more detail in "Results" section. Statistical analyses for both model 1 and model 2 showed that there were significant differences in activity sensor value range regarding each activity type for X and Y acceleration, as well as total data. However, that didn’t give us an insight necessary to determine a separation point for each activity type, it just confirmed that there were indeed different activity sensor values associated to each type. There was an exception with X axis acceleration where a significant difference in activity sensor value ranges for "low activity" and "medium activity" did not exist. This was visible from the categorization to activity value ranges. Range for the passive behaviour remained the same because that proved to be the range with highest percentage of observed passive behaviour. Both models included 94.3%, 85.1%, and 87.9% for X acceleration, Y acceleration, and total activity respectively. The difference was in ranges for "low activity” and "medium activity". Model 1 defined "low activity" as a time interval where >50% of active behaviours was feeding, and "medium activity" as a time interval where >50% of active behaviours was walking. It followed the passive-active model where passive was defined as a time interval where >50% of total time was sleeping, standing, sitting, and/or resting, and active as a time interval where >50% of total time was walking and/or feeding. The results for active behaviours were similar, except for data for X acceleration where "low activity" had the accuracy of 53.5% with 30.2% defined as passive behaviour, while "medium activity" had the accuracy of 25% with 50% defined as "low activity" behaviour. This basically meant that in the "active" range of activity sensor values there was too much overlapping between low and medium activity, and they couldn’t be differentiated from one another. Acceleration on Y axis had a better accuracy for "medium activity", but a lower than expected accuracy for "low activity". And finally, total activity had a higher accuracy for "low activity", but a slightly lower one for "medium activity". It should again be noted that some of the lower percentages could be attributed to the low amount of data for active behaviours. This was also why the range for "low activity" had to be limited to only 23 counts, because there would not be enough "medium activity" data if the limit was higher. The total count of "medium activity" data was only 11 - 12 counts. Because of this, I wanted to see if it could be possible to achieve a higher percentage of data that would correlate with already determined activity value ranges by constructing model 2 where "medium activity" was defined as a time interval where >70% of active behaviours was walking. It resulted in slightly higher percentages for "low activity" ranges than with model 1, but with lower percentages for "medium activity". Again, this could probably be contributed to a low count of active behaviour data, namely lack of longer durations of walking within 5-minute time intervals.

It was not possible to decide if model 1 or model 2 could be used to safely differentiate between lower or higher durations of feeding and walking within one interval, and further analyses would require a significantly larger amount of higher activity values data. Therefore, the application of these results on bears in the wilderness could be possible with further research, and in combination with GPS location and movement data (Shephard et al. 2008; Gottardi et al. 2010), and preferably indirect observation of behaviour by locating and documenting denning or feeding sites that bears frequent (Gervasi et al. 2006; Kozakai et al. 2008). However, since I had access to activity sensor data for a non-captive bear, I was able to make a theoretical application of its passive and active behaviours based on the two models described in this thesis. Bear activity is a result of its environmental conditions such as availability of food (Clevenger et al. 1990), which change with passing of seasons. It follows that the activity level and intensity will also be dependent on seasons. The activity is at its lowest point during winter when bears hibernate (Swenson et al. 2000), with spring and mating season, bears start foraging, but spring is also marked by low food intake (Naves et al. 2006). In summer they increase activity and feeding, with late summer and autumn marked by intensive foraging and high food intake as a preparation for hibernation (Welch et al 1997). Non-captive bear used in this study was fitted with a GPS collar that recorded activity data for the period of approximately two years. It was possible to analyse seasonal data for 2015. and 2016., with exception of winter in 2016. as the GPS collar stopped transmitting in autumn 2016. Application of two activity models to seasonal data showed that activity patterns were similar in spring and summer, while low activity and medium activity percentages varied in autumn. Percentage of both active behaviours was at its lowest during winter, as expected. When looking at monthly categorization it was somewhat easier to follow a trend of increased "low activity" percentages during autumn, which was expected due to high food consummation as a preparation for winter. "Medium activity" was highest during late spring and summer of 2016, consistent with the mating season and periods of intensive foraging (Welch et al 1997).

5. CONCLUSION

It was not possible to determine if the activity models could be used to predict and explain activity patterns of non-captive bears, and since the analyses was based on percentages of different behaviours, the possibilities of lower counts equalling foraging or idle walking could not be excluded. Digging and other high energy behaviours could increase the count even though the bear was not necessarily walking and covering large distances, and without availability of visual data and GPS locations, the results remained inconclusive. A more integrated approach is required prior to the interpretation of the activity patterns of the non-captive bears. Results may be affected by the collar tightness, position, and even behaviour of individual bears. Furthermore, due to lack of activity sensor data for counts higher than 120 in the captive bear, it was questionable whether the models could be applied as such to data that contains maximum counts (255). Another concern was an extremely low count of "low activity" entries, which was likely due to a small activity value range assigned to that activity type, and not necessarily related to actual behaviour or activity patterns in the wild. More research should be considered, especially concerning behaviours attributed to higher activity values, including observation of captive bears throughout all seasons and for longer periods of time, and having more than one individual fitted with the GPS collar. One of the major shortcomings in the usage of activity sensors in behaviour studies is averaging of counts into 5-minute intervals. It is unlikely that a bear will spent 5 minutes consistently walking or running, and the sensor may not pick on shorter bouts of higher activity behaviours. However, a new sensor type (VERTEX plus activity sensor) has been developed that constantly sends feedback of data without averaging the counts, which could prove more useful for this type of study (http://www.vectronic-aerospace.com). Gervasi et al. (2006) also suggest that placing activity sensors on different areas of the animal's body might provide better results than placing it on the animal's neck. Data gained through more extensive observation, using GPS locations to determine ecologically important areas and their purpose, and comparison between different methods of data recording, could greatly benefit a more accurate prediction of activity patterns and behaviour in wild bears.

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http://www.vectronic-aerospace.com/wp-content/uploads/2016/04/Flyer_VERTEX_Plus.pdf

CURRICULUM VITAE

KATARINA PERKOVIĆ
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EDUCATION

9/2015-1/2018 **Master Degree in Experimental Biology (Zoology)**
University of Zagreb, Faculty of Science, Department of Biology

Thesis: "*Analyses of Brown Bear (Ursus arctos Linnaeus, 1758) activity in natural conditions and captivity*"
Supervisor: Assoc. Prof. Dr. Sc. Josip Kusak
Co-Supervisor: Assoc. Prof. Dr. Sc. Davor Zanella

9/2012-9/2015 **Bachelor Degree in Environmental Science**
University of Zagreb, Faculty of Science, Department of Biology

Undergraduate study of Environmental Science combines biological, geological, and geographic components and aims to explain the fundamental biological, geological and geographic principles and mechanisms at all integrative levels of environmental organisation.
Thesis: "*Eusociality in African Mole-Rats*"
Supervisor: Asst. Prof. Dr. Sc. Duje Lisičić

9/2008-7/2011 **Master of Science in Physics**
University of Zagreb, Faculty of Science, Department of Physics

Unfinished degree.

SCOLARSHIPS

Erasmus+ Programme
Scholarship for an international traineeship at Liverpool John Moores University, United Kingdom, summer 2016.

CONFERENCES/PRESENTATIONS

7/2017 **20th Symposium of Biology Students in Europe (SymBioSE), Lund, Sweden**

"Investigation into micro-habitat preferences of colour polymorphic Gouldian finches"
- oral presentation

4/2016 **2nd Symposium for Students of Biological Orientations (SiSB2), Zagreb, Croatia**

- attended

EXPERIENCE AND TRAINING

7/2016-9/2016 **Erasmus+ Traineeship**
Liverpool John Moores University, Faculty of Science, School of Natural Sciences & Physiology, United Kingdom
Research: *"Investigation into micro-habitat preferences of colour polymorphic Gouldian finches"*
While working on this project, I gained experience in handling and measuring birds, behavioural observations, data analyses using statistical methods, and setting up my own experiments.
Supervisor: Dr. Claudia Mettke-Hofmann

6/2016 **Zoology Field Course**
University of Zagreb, Faculty of Science, Department of Biology
A week-long course for students of Zoology, during which we got acquainted with various sampling and monitoring methods for wildlife in Gorski Kotar region, methods for assessing population size, applying identification keys for vertebrates, and vocal identification for birds.

5/2015 **Field Course in Biological, Geographical and Geological Environmental Protection**
University of Zagreb, Faculty of Science, Department of Biology
A week-long course for undergraduate students of Environmental Science on Istrian peninsula with the focus on biogeography and biomanipulation, sampling marine life and freshwater fish.

2/2015-6/2015	**Laboratory skill training** University of Zagreb, Faculty of Science, Department of Biology Research on the behaviour of the Balkan Snow Vole (*Dynaromis bogdanovi*). I observed and characterized various behavioural categories from recordings of captive voles using Solomon Coder software. Supervisor: Asst. Prof. Dr. Sc. Duje Lisičić
4/2013, 4/2014	**Educator at the scientific event for the public – "Noć Biologije"** University of Zagreb, Faculty of Science, Department of Biology Participated in educational workshops: "*Honeypot Ants: Life Cycle and Specialized Caste*" and "*Ants of Medvednica and Invasive Ant Species in Zagreb*".
5/2013	**Educational research project - Apsyrtides 2013** BIUS (Croatian Association of Biology Students) A ten-day-long research camp with the focus on fieldwork. The goal was to inventory fauna and flora of the Croatian island Cres. I participated with the Section for Ants in inventorying ant species by using pitfall traps, food baits and manual collection of workers for further species identification in the laboratory. Food bait method was also used to observe the competition and activity of different species.
9/2013	**Ornithology Camp Nature Park Učka** A bird ringing event organized by NGO BIOM in cooperation with Nature Park Učka. I volunteered with handling and retrieving caught birds from bird nets.
2012-2015	**Member of BIUS (Croatian Association of Biology Students), Section for Ants** Gained knowledge and experience in fieldwork, mounting/pinning of ants, determination of ant species using a stereo microscope and dichotomous identification keys.

SKILLS

Research:	- Experience in handling laboratory animals (IV, intradermal and subcutaneous injecting, humane methods of euthanasia)

- Experience in handling captive birds (catching, taking standard morphological measurements such as wing length, tarsus length, body mass, and assessing moult stage in adult birds)

- Experience in handling wild birds (handling and retrieving seagulls and small songbirds from cannon and mist nets)

- Knowledge in identification and ecology of ants in Croatia

- General knowledge in identification and ecology of birds

- General knowledge in sampling and monitoring methods

- Behavioural monitoring (birds, small rodents, brown bear)

- Molecular methods (DNA isolation, PCR, electrophoresis, chromatography)

- Dissection

Computer: - Microsoft Office (Excel, Word, Powerpoint), statistical software R, SPSS Statistics, Solomon Coder, VirtualDub, Adobe Photoshop CS6

LANGUAGES

- Croatian (native)
- English (C1)