Quantifying Finer-scale Behaviours Using Self-organising Maps (SOMs) to Link Accelerometery Signatures With Behavioural Patterns in Free-roaming Terrestrial Animals.

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Research Article

Abstract

Collecting quantitative information on animal behaviours is difficult, especially from cryptic species or species that alter natural behaviours in the presence of humans. We develop a methodology that can precisely classify finer-scale behaviours in free roaming animals. We deployed harness-mounted tri axial accelerometers on 10 free-roaming domestic cats (*Felis Catus*) over eight days. We also tested two treatments using a prey protector device designed to reduce prey capture.

We aligned accelerometer traces collected at 50Hz with video files (60 fps) and labelled 12 individual behaviours, then trained a supervised machine-learning algorithm using Kohonen super Self-Organising Maps (SOM). The SOM was able to predict individual behaviours with a ~ 99% overall accuracy. There was a significant effect of sample size, with precision and sensitivity decreasing rapidly below 2,000 1-second observations. We were also able to detect a behaviour specific reduction in the predictability when cats were fitted with the prey-protector device indicating the it alters biomechanical gait.

Our results can be applied in movement ecology, zoology and conservation, where habitat specific movement performance between predators or prey may be critical to managing species of conservation significance, or in veterinary and agricultural fields, where early detection of movement pathologies can improve animal welfare.

Introduction

Bio logging devices, in particular tri-axial accelerometers, can be used to investigate finer-scale behaviours and the biomechanical patterns of movement which are relevant to species conservation planning. (Houghton et al., 2009; Ryan et al. 2013). However, research using accelerometry to identify the finer-scale behaviours associated with individual activities of a species is currently scarce (Fannjiang et al., 2019). Fine scale behaviours can be characterised as biomechanic movements of short duration (eg. pouncing and jumping). Behaviours measured with accelerometers quickly produce millions of data points, making analysis of acceleration data a time-consuming task. This is one of the main challenges when using this technology for the study of animal behaviour (Shepard et al., 2008; Brown et al., 2013). Despite the improvements in technology to understand animal movements, an easy-to-use, effective tool to process and identify finer-scale behavioural patterns from accelerometer data is currently lacking.

Increasing attention has focused on automated behavioural classification using machine-learning (ML) techniques to classify the behaviour of animals from accelerometry (Chimienti et al., 2016). Machine learning techniques such as support vector machines (SVMs), random forest (RF) and artificial neural networks (ANNs), provide computationally powerful methods of data classification that can detect complex patterns that are not evident to the human eye. Thus, the models can identify intrinsic differences between behaviours or locomotory types when applied to acceleration data (Carrol et al., 2014; Martiskainen et al., 2009). Accelerometer data has been used to compare machine learning methods in a study by Nathan et al 2012. Supervised methods (ANN, RF, SVM) were implemented and

compared with linear discrimination analysis (LDA) as a baseline for classifying seven behavioural modes in free ranging griffon vultures. All machine learning methods were found to accurately classify behaviour (80−90%) and all non-linear methods outperformed LDA.

Self-Organizing Maps or (SOMs) are a type of ANN which can efficiently create maps of multi-dimensional and complex data in order to approximate the probability density function of the input data and show the data in a more comprehensive fashion and in fewer dimensions (Kohonen, 2001; Chon 2011). SOMs have been implemented broadly in ecological sciences, the methodology having advantages for information extraction (i.e., without prior knowledge) and efficiency of presentation, (i.e., visualization)(Chon 2011). The algorithm is able to map high-dimensional data to a 2-dimensional map display in such a way that similar data are located close to each other on the map (Pampalk, Widmer & Chan 2003); allowing simple interpretation of large data sets. Use of SOMs in ecological behavioural literature have primarily analysed behavioural change in animals in response to environmental stressors (e.g., toxic chemicals)(Chon et al., 2004, Park et al., 2005, Ji et al., 2007; Chon 2011). The method was also recently applied to classify behaviour in the human gait signature. Lakany (2008) successfully used wavelet and SOMs to correctly classify pathological cases which clinicians, due to the complexity of the impairment, have difficulty in accurately diagnosing. The SOM extracted features that successfully discriminated between those individuals with and without impaired locomotion (Lakany, 2008; Chon 2011).

There is limited research in animal behaviour that uses the practice of pairing the trained finer-scale individual movements from accelerometer trace data sets and applies it to trained supervised (ML) SOM algorithms, to produce higher levels of accuracy in detecting how different species are behaving on the basis of independent unsupervised data sets (Carroll et al., 2014; Fannjiang et al., 2019; Watanabe & Takahashi 2013). Here we demonstrate the use of SOMs to visually represent and compare 12 different behaviours in free roaming domestic cats.

Domestic cats are highly effective hunters, displaying variations in hunting tactics and a range of prey-specific behaviours (Fisher et al., 2014; Dickman and Newsome 2015). In order to reduce this impact of domestic cats on wildlife many manufacturers have attempted to create prey protector devices which reduce the effectiveness of hunting in domestic cats. One example is the CatBib which was shown to reduce prey capture by 81% (Calver et al., 2007). These studies suggest that the CatBib™ prey protector device could disrupt in some way the killing behaviours of cats (Goods Inc, 2000; Calver et al., 2007; Lilith et al., 2010); however, there is no clear evidence or research on how or why this occurs. Without a mechanistic understanding of how the CatBib™ influences the gait or movements of cats, it is challenging to ascertain whether the CatBib™ causes a reduction in overall hunting behaviours, or simply acts as a visual deterrent. We therefore further demonstrate the effectiveness of the SOM model to distinguish not only individual behaviours, but the ability to detect behaviour specific changes in movement which result from the presence or absence of the bib.

We studied the behaviours of free-roaming domestic cats (*Felis catus*) within South East Queensland, Australia, with a particular focus on developing tools to allow fine-scale movement behaviours of small animals to be collected and easily displayed. We used accelerometer trace data to identify behaviours, using a supervised machine learning Self-Organising Map (SOM) algorithm to accurately predict the foraging behaviours of domestic cats (Campbell et al., 2013). Our objectives were to determine: 1) how accurate SOMs are in predicting fine-scale behaviour and 2) how the CatBib™ influences behavioural signatures in the accelerometer trace, if at all. It is expected that the accelerometer signature will be modified while wearing the CatBib™ when cats are free roaming, with hunting behaviours that display intensive acceleratory bursts of short duration such as jumping and pouncing to be most impacted.

Methods

Data collection

Data were collected on the Sunshine Coast region in Queensland, Australia (-26.65º S, 153.07º E), from February – April 2019. All methods were carried out in accordance with relevant guidelines and regulations. All experimental protocols and methods were approved and carried out in compliance with the ARRIVE guidelines under the approval of the University of the Sunshine Coast (USC) Animal Ethics permit (ANA/16/109T); Human Ethics permit (A181114) and in conjunction with the Sunshine Coast Council (SCC) Local Law permit (OM18/19).

Animals used in the trials

We recruited 10 domestic cats through an approved media release (males n = 8; females n = 4; weight 2.8–8.4 kg; Age 1.5–12 years; body length 38–53 cm; foreleg length 16–19 cm). As per the Sunshine Coast Council local law requirements, all cats had to be neutered, registered and microchipped to participate in the study.

Equipment

We fitted each cat with a retail harness, to which we attached a tri-axial accelerometer (AX3; Axivity, Newcastle University, UK; 23 x 32.5 x 8.9 mm; 11 g) using cable ties (Fig. 1a). The accelerometer was initialised using the Open Movement Graphical User Interaction application (OMGUI; V1.0.0.37). Because a trade-off exists between data resolution and battery life, we logged data at 50 Hz and with a dynamic range of ± 8 g, with a 13-bit resolution, similar to a previous study (Godfrey et al. 2015). When combined with the in-built memory storage capacity of 512 MB, and battery limitations, this configuration resulted in a maximum of 8 – 14 days of data collection. The quartz Real Time Clock (RTC) and calendar provided a timestamp with a frequency of 32.768 kHz and a precision of ± 50 ppm, with manufacturer specifications indicating a drift of 0.18 seconds per hour. To overcome this drift over the eight days, we calibrated devices by video recording the signals of five claps/taps on the device, at the start and end of each individual data collection period, and also at random times during the day.

We positioned the accelerometer on the scapular brace-strap of the harness, inverted such that the accelerometer was on the sternum of the cat (Fig. 1a–c). Field trials over four months on four cats in the study determined that this position, in comparison with mounting on the dorsal cranial median plane, did not interfere with the animals' balance; it also removed all of the abnormal movement behaviours and unnecessary discomfort to the cat (Ryan et al., 2013). The positioning of the logging device on the frontal anterior, median plane, resulted in the primary axis for fore-aft (surge), lateral (sway) and dorso-ventral (heave) movement to be reflected in the X, Y and Z signals, respectively (Fig. 1c).

The accelerometer harness was used in conjunction with the CatBib™ for the relevant treatment periods. The total combined weight of the harness, accelerometer and Catbib™ came to 34.1 g, all cats weighed 2.8 kg or more, weight of equipment did not weigh above 1.2% of total body weight of any cats studied. The CatBib™ is a prey protector device, manufactured from a lightweight, washable neoprene material, that is attached to a cat's safety collar (Fig. 1b). The dimensions of the bib are 17.5 mm x 17.5 mm x 6.5 mm, with a total mass of 23.1 g and it is purple in colour. All cats adjusted to the harness and CatBib™ within the first hour of deployment and no subsequent adjustments were required. All cats had unrestricted access to roam freely outside during the eight days of field trials.

To capture training data, each cat was filmed with a GoPro + 3 Hero device (H.264–1920 x 1080; f/2.8; 60 fps), undertaking natural or stimulated active behaviours through play (Fig. 1b). These activities or behaviours were manually documented to track the activity, date and the timestamps. We conducted two treatments over the eight days: in the first, cats were fitted with CatBib™, whereas in the other, bibs were not worn. Each treatment was conducted for four consecutive days, and the sequence of treatments for each cat was randomised. The accelerometer device on the harness was left on the cats for the entire field trial and recorded continuously for the eight days (~ 192 hrs per cat; total = 2304 hrs).

Data analysis

Each accelerometer trace file was exported as a raw binary file through OMIGUI and imported into a custom-built MATLAB GUI. To build our training dataset, the video file timestamp information, determined using Mediainfo (version 18.08, 2018; Martinez et al. 2002), was used to define the start time for a subset of the accelerometer trace, and the video length to define the end point (Supp. Figure 1). Offsets between the accelerometer trace and video files were determined using the closest calibrated tap signal trace for each day. We were able to watch each video file in synchrony with the accelerometer trace, and manually annotate each movement/activity from the video files to the accelerometer subset (Clemente et al., 2016) (Supp. 1.1. Matlab interface instructions) (Supp. Figure 1).

We grouped activities according to behaviour into three classes: Sedentary, Eating and Locomotive and Hunting. We further subdivided each group into behaviours. Sedentary included lying, sitting, grooming and watching; Eating and Locomotive included – eating/drinking, walking, trotting; and for Hunting – galloping, jumping, pouncing, swatting, biting/holding (Supp. Table 1).

The accelerometer trace was then further divided into rolling epochs of 50 samples in length, using 1 second duration at 50 Hz to ensure intensive acceleratory bursts of short duration such as jumping and pouncing are captured. The activity/movement with the maximum duration within each epoch was assigned as that epoch's label. Raw accelerometer data in each epoch was assigned as that epoch's label. Raw accelerometer data in each epoch was summarized using 26 of the most effective variables for model accuracy identified by Tatler et al. (2018). We included: axial acceleration (X, Y, Z); mean acceleration (X, Y, Z); minimum acceleration.(X, Y, Z); maximum acceleration (X, Y, Z); standard deviation of acceleration (X, Y, Z); Signal Magnitude Area, minimum Overall Dynamic Body Acceleration (ODBA); maximum ODBA, minimum Vectorial Dynamic Body Acceleration VDBA; maximum VDBA, sum ODBA; sum VDBA; correlation (XY, YZ, XZ); skewness (X, Y, Z); and kurtosis(X, Y, Z) (Tatler et al. 2018) (See Supp. Table. 3 for a detailed description of each variable). Finally, we coded the two treatments: Bib_{ON} and Bib_{OFF} and exported this information as the training data set.

Classification modelling

To determine whether we could predict cat hunting behaviours, we analysed the training data sets using a Kohonen super Self Organising Map (SOM) in the R package 'Kohonen' version 2.0.19 (Jahan et al., 2013; Wehrens & Kruisselbrink 2018).

Machine learning models such as Random Forest and Support Vector Machines each provide computationally powerful methods of data classification, however each method is not equal in how it visualises its output. SOMS have been used in behavioural studies (Chon et al., 2004, Park et al., 2005, Ji et al., 2007; Chon 2011) for their ability to efficiently create easily interpreted maps and identify patterns of behaviour. In this study, a Self-Organising Map algorithm was chosen for its efficiency in visualising multi-dimensional and complex data onto an easily interpreted two dimensional map output. SOMs also have the ability to visualise which variables are most influential with the use of component planes (Fig. 3b-e)) and unlike other models mentioned, SOMs use cluster analysis which in this study aids in identifying similar behaviours and visualising them closer together (in clusters) on the map output.

To prepare data for the SOM function a random sample of the classifiers for the trained data were extracted, along with their associated behaviour, and combined into a list with 2 elements (measurements and activity). This list was then input into the function supersom.R function, with the grid argument defined using the somgrid.R function [e.g. supersom(TrainingData, grid = somgrid(7, 7, "hexagonal"))]. The 7 x 7 grid function was chosen based on 12 behaviours, with 4 elements for each behaviour (12 x 4 = 48). For map symmetry we rounded the map output to 49 hexagonal spaces to spread the output data in a 2-dimensional space (Jahan et al. 2013; Schulz & Dominik, 2013; Stefanovic & Kurasova (2011b). The output of the supersom function was then used as the input into a predict.R function, with the newdata argument directed to a testing data set, which was a similar 2 element list containing all samples not included in the training data set [e.g. predict(ssomOutput, newdata = testData)].

We then built a confusion matrix from the output of the predict function, using the table.R function with predictions compared with the testData set [e.g. table(predictions = ssom.pred$predictions$activity, activity = testData$activity)]. The confusion matrix was then finally used to compute four specific accuracy metrics – sensitivity (or recall), precision, specificity, as well as overall accuracy.

To identify relationships between the size of training dataset, we trained a randomised subset of the Bib_{OFF} training data, to predict the remaining Bib_{OFF} data from all cats. We tested 35 different subset sample sizes from 100–100,000, replicating each sample size ten times (with replacement) to determine variation at each sample size.

We then tested the extent to which accelerometer traces are modified by the presence of the CatBib™. This modification was indicated by a change in overall prediction accuracy of the SOM between Bib_{OFF} and Bib_{ON} treatments. To do this, we trained the SOM using a subset of the trained data for Bib_{OFF} and tested it against annotated classified Bib_{ON} samples. In order to statistically compare results from bootstrap resampling, we took the median among bootstrap samples as the estimate of performance and quantified uncertainty using the corresponding 2.5th and 97.5th percentiles to represent credible 95% confidence intervals (CIs). If CIs for any pair of estimates (medians) do not overlap, then this is evidence of a significant difference between the estimates. If, however, one estimated median fell within the confidence interval for another estimate, then this was used as evidence of a lack of significant difference. For all other outcomes, differences are equivocal, and we interpreted them tentatively on the basis of the relative overlap in CIs.

Results

Collected data

We collected 2,304 hours of data from 10 cats over a period of four weeks which included 103.47 hours of labelled data from the two CatBib™ treatments. This resulted in 212,789 1-second epochs of labelled data in the Bib_{OFF} condition, and 159,724 1-second epochs of labelled data in the Bib_{ON} condition. The output resulted in high overall accuracy (99.7%) when a random sample of 20,000 epochs was included (Supp Table 2). Specificity was similarly high (99.8%), with slightly lower levels of precision (93.9%) and sensitivity (94.3%).

Model performance and behaviour detectability

Of the 212 789 samples in the Bib_{OFF} data we took random sub samples between 100–100,000 to test how accuracy changes with sample size. The sensitivity of the model increased dramatically in behaviour detection for sample sizes between 2,000 and 10,000 samples but plateaued after 20,000 samples (Fig. 2). However, lower sample sizes of less common behaviours such as galloping (76%) and pouncing (83%) may have hindered the model's ability to detect overall accuracy of these behaviours (Supp

Table 4). In contrast, activities which were common: lying (99%), walking (99%) and eating (99%) had the greatest accuracy even at very low sample sizes < 1000 epochs long.

Figure 3(a) illustrates the SOM output, using the plot.kohonen.R function with the 'type' argument set to codes. The colour of each triangle indicates which activity is represented in the cell, and proximity of cells to each other indicates the similarity of their signature. Behaviours which share similarity can be seen clustering together; for example activities which include movement; walking, grooming and swatting in the top right of the map. Sedentary activities lying and sitting are shown clustering to the centre bottom of the SOM output. The bold lines between cells in Fig. 3a are defined using hierarchical clustering using the distances between codebook vectors in the SOM output [e.g. cutree(hclust(object.distances(ssom, "codes")),12)].

Figure 3b−e illustrates the SOM output using the plot.kohonen.R function with the type argument set to property. This produces component planes for each of the classifiers with heat maps indicating the relative importance of classifiers among different behaviours. Four example component planes are shown. The SumVDBA is shown associated with jumping, Max Z is associated with jumping and biting, the correlation between X and Z was associated with eating and grooming, while the mean X trace was associated with watching, walking, lying and eating.

Biomechanical effects of the CatBib™

For further analysis we used a random subsample of 20,000 1-second epochs, which reflected a compromise between accuracy and computational time. Using the trained subset of Bib_{OFF} data, we tested whether the bib had any biomechanical effect on the labelled Bib_{ON} data set (i.e., whether the predictability of activities declined for the Bib_{On} relative to the the Bib_{Off} treatment). This analysis was repeated 1,000 times for Bib_{OFF} vs Bib_{OFF} data, and similarly for Bib_{OFF} vs Bib_{ON}. Non overlapping CI's indicate the biomechanics in activities eating and walking were affected by the presence of the bib.

Discussion

This paper developed a method to accurately identify finer-scale behaviours from accelerometer trace signatures. Few studies have been able to identify fine-scale behaviours with high accuracy (Brown et al. 2013; Fannjiang et al. 2019; Ladds et al. 2017; Pagano et al. 2017; Ryan et al. 2013; Tatler et al. 2018; Watanabe & Takahashi, 2013). Our objectives were to determine how accurate SOMs are for predicting fine-scale behaviours from accelerometer signatures in free-roaming domestic cats and whether these signatures are influenced by the CatBib™ prey protection device.

We compared the accuracy of SOMs with other studies that used comparable classification models. Carrol et al. 2014, applied accelerometer data to a support vector machine (SVM) to identify a prey capture signature for little penguins, the study showed that fine scale foraging behaviours that correspond to transient events lasting less than a second can be detected with a machine learning model such as an SVM with an accuracy of 84.95 ± 0.26% (mean ± s.e.). Research by Fehlmann et al. (2017)

uses a random forest model (RF) to analyse fine scale behaviours in foraging and locomotion on primates using tri axial accelerometer data. The machine learning analysis identified all behaviours with an average precision of 88.3% (± 8.5%) and a mean recall of 70.7% (± 29.3%) across all behaviours. Tatler et al. (2018) used a cross-validation method comparing performance of four commonly used classification models (Naïve Bayes, SVM, k-nearest neighbor & RF) at a sampling frequency of 1 Hz to identify 14 behaviours observed from three captive dingos (*Canis dingo*). The True skill statistic score was highest with overall accuracy 87% when using a random forest model.

The SOM delivered a consistently high (~ 99%) model accuracy from free-roaming domestic cats across all behaviours at a sampling frequency of 50 Hz, at least where sample sizes are greater than ~ 2000. The SOM has an added advantage over other machine learning models, in its ability to easily create heat mapped component planes (Fig. 3) b-e) which help to determine the contribution of each variable to cluster structures and the correlation between the different variables in the dataset (Pacella, Greico & Blaco 2016). Visualising which variables are colinear is useful in determining which to include in the model, and which variables have the greatest explanation in the output. The clustering capability of similar behaviours is also a strong visual advantage provided by the SOM. The dissimilarity in behaviours can be seen between watching and eating which are clustered furthest apart in the top left hand corner and bottom right hand corner. Closer together we can see grooming and swatting sharing the top right hand corner, indicating these behaviours are more alike. Our results have demonstrated an average overall model accuracy of ~ 99% when samples sizes exceed 20,000. Watching and walking both have large representation from the dataset on the map and do not appear clustered within other behaviours. With our dataset containing a larger amount of these behaviour data points, the SOM has efficiently recognised these behaviours by clustering them strongly together. However, limitations of the SOM network are illustrated in the bottom left hand corner. The behaviours with low sample sizes are represented by mixed triangles that indicates the SOM network was unable to consistently identify the behaviour with high precision or sensitivity. These behaviours included pouncing (n = 3884) and galloping (n = 715), which sample sizes were significantly lower than other behaviours (Supp Table 4). Sufficient data is required in order to develop strong clusters and give accurate precision. Where sample sizes were low in our data set, precision and sensitivity were weakest and more likely to produce a false positive or false negative output (Fig. 2.). Future studies should focus training data collection towards relatively rarer behaviours that are associated with hunting and foraging activities such as in our data set galloping and pouncing.

We detected a reduction in predictability when the SOM was trained using Bib_{OFF} data and tested on the Bib_{ON} condition. Further, this reduction in predictability was inconsistent among behaviours, allowing us to determine which behaviours were most influenced by the presence of the Bib_{ON} (Fig. 4.). Of these behaviours, eating and walking had the overall largest effect size when all of the cats were considered. This suggests that the CatBib™ is interfering with these behaviours and, therefore, each cat has had to adjust their biomechanical movement of these activities. This effect was not unexpected and is likely due to the proximity of the cat bib to the anterior limbs. Walking is likely affected by a physical interaction of

the limbs with the bib as they swing through each stride. Similarly, eating is likely to be greatly affected by the bib interacting with the head when the cat adopts a sitting posture during feeding and the bib hangs in front of, or even over the food. Yet there was little evidence that activities associated with hunting behaviours, including galloping, swatting and pouncing, were influenced by the bib (Fig. 4). This may reflect the low predictability of these activities. The accuracy of these behaviours may not have been greatly altered as these are powered by the hind feet, and therefore less likely to be affected by the presence of the bib. If the latter is true, then this may suggest the reduced kill rate while wearing the bib can be primarily attributed to increased visual exposure of the cat, rather than biomechanical alterations to the gait. It must also be considered, given our results, the reductions in kill returns reported by Calver et al. (2007, 2011), might be because of interference with bite/hold activity, as cats may be able to kill, but not carry prey. Such a possibility requires further substantive investigation.

The SOM demonstrates a highly accurate (~ 99%) model when classifying fine-scale behaviours from a small (< 8 kg) terrestrial predator. We show that the self-organising map algorithm performs well if not better than other machine learning models when overall accuracy is compared. The advantages of SOMs have been demonstrated through visualisation of output, of both the map and its respective component planes, and the strength in its ability to determine weights of individual classifiers. Finally, the SOM has shown its ability to detect behaviour specific changes in response to the CatBib™ prey protector device. SOMs are highly underrepresented in behavioural classification despite the strengths of the model. These features combined with relative ease of implementation make SOMs highly suitable for work in ecology and this study provides a template for future studies in ecological feature detection and classification.

Declarations

DATA AVAILABILITY

Competing interests

The authors declare no competing interests.

ACKNOWLEDGMENTS

AUTHORS CONTRIBUTION STATEMENT

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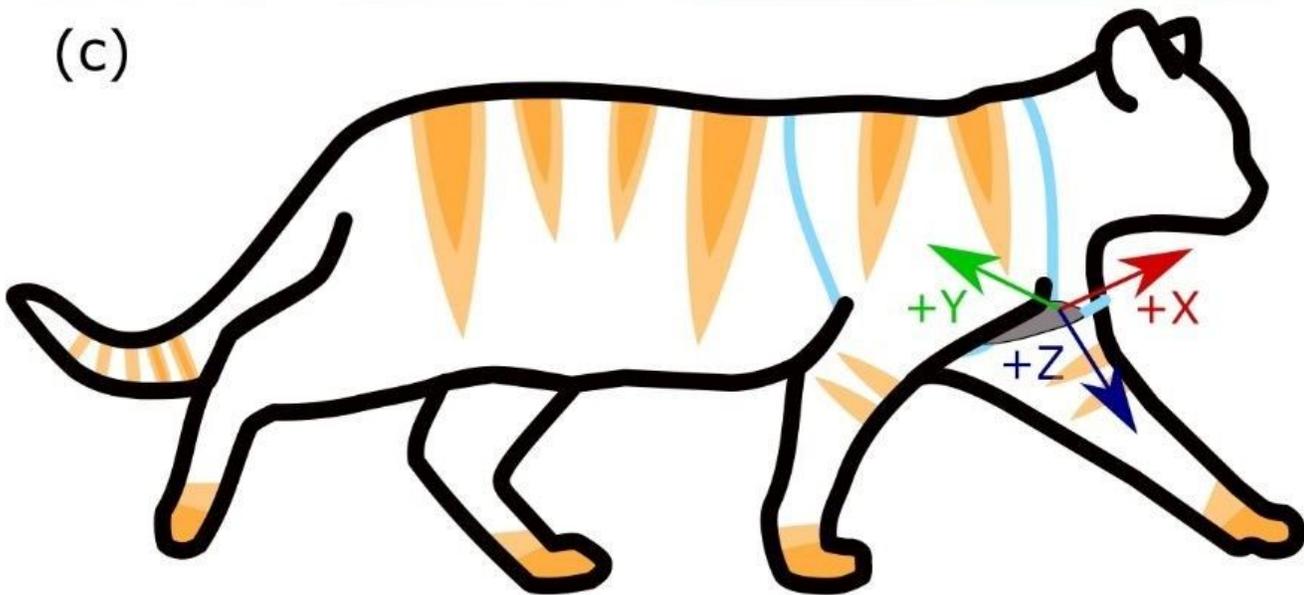
Figures

Figure 1

(a) The anatomical position of the accelerometer (AX3) on the sternum of the cat. (b) The activity of swatting stimulated by the use of a feather. (c) The axis orientation of the accelerometer planes, which are represented in the accelerometer trace data in the MATLAB interface.