Capability of movement features extracted from GPS trajectories for the classification of fine-grained behaviors

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Abstract

Recent advances in tracking technologies provide an unprecedented opportunity for a better understanding of animal movement. Data from multiple sensors can be used to capture crucial factors deriving the behaviors of the animal. Typically, accelerometer data is used to describe and classify fine-grained behaviors, while GPS data are rather used to identify more large-scale mobility patterns. In this study, however, the main research question was to what extent fine-grained foraging behaviors of wading birds can be classified from GPS tracking data alone. The species used in this study was the Eurasian Oystercatcher, *Haematopus ostralegus*. First, a supervised classification approach is employed based on parameters extracted from accelerometer data to identify and label different behavioral categories. Then, we seek to establish how movement parameters, computed from GPS trajectories, can identify the previously labeled behaviors. A decision tree was developed to see which movement features specifically contribute to predicting foraging. The methods used in this study suggest that it is possible to extract, with high accuracy, fine-grained behaviors based on high-resolution GPS data, providing an opportunity to build a prediction model in cases where no additional sensor or observational data on behavior is available. The key to success, however, is a careful selection of the movement features used in the classification process, including cross-scale analysis.

Keywords: Movement analysis, GPS, accelerometer, foraging behavior, movement parameters, classification

1   Introduction

Classification of movement trajectories into different behavioral categories has become a recent trend in many domains, including e.g. movement ecology, transportation, and urban management. In ecology especially, behavioral classification is an important analysis step, because knowledge about behaviour provides important input to many inferences about physiology, energy balance, and evolution of particular species. While various types of data are being used for animal behavior classification, the use of features based on movement trajectories (e.g. GPS) is still quite uncommon (see [18]). The main reason for this has been that when the goal is to distinguish between behaviors (especially fine-grained behaviors, e.g. foraging vs. non-foraging), the temporal sampling rate is typically low or irregular in relation to the variability inherent to the movements that are considered. However, due to recent advances in tracking technologies, it has become feasible to collect high-resolution GPS and sensor data on a more regular basis. For example, GPS has been integrated into operational systems with other sensor technologies to collect temperature, activity, proximity and mortality data from terrestrial species and birds [1, 19, 21].

This study aims at developing a classifier to identify foraging behavior in a shorebird, the Eurasian Oystercatcher (*Haematopus ostralegus*), based on GPS trajectory data. This species has been intensively studied ([6]) to answer questions on e.g. foraging ecology, resource use and territoriality in shorebirds. The GPS trajectory data for individuals may be more accurate and less biased than the sighting or experimental data that are available from previous research

and may thereby lead to more robust answers. Especially the time spent on foraging as well as foraging locations form important variables to measure foraging strategies and efficiency.

Accelerometer data can be used to identify various behaviors of an oystercatcher, including foraging [18], the same way as depth loggers are used to record 'dives', salinity sensors to record 'being in the water', or light sensors to record 'being in a burrow' [7, 9, 10, 13, 17]. However, accelerometers are not yet in widespread use today and a lot of trajectories with location-only information have been collected and will continue to be collected. According to Movebank (www.movebank.org) as one of the major repositories of animal movement, more than 90% of the data collected there is location-only. Therefore we attempt to develop features and a classifier that is based exclusively on location data. In order to do so, the model of [18] is first used to generate the behavioral labels and then serves as a baseline to train and evaluate the classification model that is based exclusively on movement features extracted from GPS trajectories. Thus, the main research question is to what extent fine-grained foraging behaviors, on the example of oystercatchers, can be classified from GPS tracking data alone.

2   State of the art

A variety of methods for inferring behaviors based on sensor data have been proposed. Among movement parameters computed from trajectories, velocity has been used to distinguish between traveling and resting during bird

migration [9], identification of different behavioral categories in combination with accelerometer readings [18], and distinguishing behavioral drug treatments in neuro-pharmacology [3]. A combination of velocity and direction has also been used in [20] for defining behaviorally consistent movement units. Sinuosity, on the other hand, has been used for detection of behavioral change in animal movement [16], foraging movement and activity patterns of seabirds [25], and for distinguishing between trajectories of different vehicles types [4]. Wavelet analysis has also been applied based on the values of net displacement [23] and velocity [15] for studying behavioral patterns in animal movement.

Accelerometer data, on the other hand, is increasingly being applied to characterize behavior or describe certain movements, e.g. of humans (using accelerometers on smart phones) [24], domestic animals [12], as well as free-ranging animals like birds [10, 14, 17, 18] and marine mammals [7, 13].

3   Methods

In this paper, we use a data set of combined GPS and accelerometer observations, obtained in the Dutch Wadden Sea, south of the island Schiermonnikoog on 12 individual Eurasian Oystercatchers (*Haematopus ostralegus*). The birds were tagged with UvA-BiTS devices [1], and samples from June and July 2009 as well as from May and June 2011 were used in this study. There were different sampling intervals in the samples, but for the major part of the data it was one location per 13 seconds (the second large group was with intervals of 6 seconds and the intervals were always lower than one location per 45 seconds).

We first classified the Oystercatcher trajectories as 'foraging' versus 'non-foraging' based on accelerometer data, using a classification model introduced in [18]. In [18], the model had been calibrated for the same species at approximately the same location while using the same devices. Based on the labeled data set we then started to develop features and classifiers based on GPS data only. The following (movement) features were calculated for each fix of the trajectories: distance traveled; velocity; turning angle and its dependent variables including angular velocity (turning angle over time) and meandering (turning angle over distance traveled). See [3] and [4] for some example uses of these parameters. Furthermore, two parameters indicative of path curvature were generated: sinuosity and the Multi-Scale Straightness Index (MSSI; see [16]).

A decision tree was selected for the classification process, using the implementation in RapidMiner 5, (RapidMiner, http://rapidminer.com/). A top-down procedure is applied based on the CART learner to traverse the tree [2]. Whenever a new node is created at a certain stage, an attribute is picked to maximize the discriminative power of that node with respect to the examples assigned to the particular subtree. This discriminative power is measured by the information gain ratio [2]. The information gain ratio can be considered as the importance of the selected attributes in the design of the tree. This was the reason for choosing decision trees in this study: they can give an insight into the relative importance of different movement features in the identification of behaviors,

by their appearance as a node splitter. Other machine learning methods such as SVM might even result in a slightly better classification performance (as preliminary test have shown), but since improving the classification performance was not the main objective of this study, those classification methods were not chosen. A 10-fold cross-validation procedure was applied to see how good the resulting classification performances are when different movement parameters were used as input variables. For the evaluation of the performance of classification models, we looked at different criteria, such as overall classification accuracy and Kappa values, as well as precision and recall values in the case of individual classes, specifically when we examined the foraging class.

Since the sampling intervals differed between data sets and earlier studies had demonstrated the importance of scale in the computation of movement parameters, we performed a cross-scale analysis, employing the method proposed by [11]. Values of movement parameters for each fix of the trajectory were computed across a series of sliding windows with different sizes of w, in a segment where $w/2$ fixes exist before and after the central sample point of interest.

4   Results

4.1   Attribute selection

The classification performance was first acquired individually for all parameters. At first glance, velocity and distance traveled did seem to have a large impact on the classification results, which is in accordance with the findings of the studies having used these parameters [9, 15, 20, 23]. Turning angle, angular velocity and meandering, on the other hand, were not so helpful, which might be due to the positional error in GPS observations, especially at lower speeds. For the path curvature parameters, including MSSI and sinuosity, the values were computed across different scales. MSSI is inherently a multi-scale measure and similarly to sinuosity, it gives a ratio of the beeline distance between two points of interest and the actual distance traveled. However, the difference between the measures is that distance is computed multiple times, over a variety of scales for both temporal granularity and observational window [16]. We chose a granularity value of 2 and window sizes of 4, 8, 12, 16, 20 and 24, respectively. When individual sets of MSSI values were used, they were not helpful in distinguishing between classes, but as will be shown later, when geographic location is integrated (latitude and longitude), they do show a great potential in improving the results.

The same cross-scale approach was employed for sinuosity. The window sizes chosen for calculation of sinuosity start from the surrounding fixes (window size of 1), increasing up to 7 points before and after (1, 2, 3, 4, 5, 6, 7). Then, each set of sinuosity values computed at different scales were considered separately as input features in the classification, to see how the performance and the resulting decision tree would vary. We used the 3-class category (no locomotion, terrestrial locomotion and fly) of [18] in this part, as we wanted to investigate the importance of scale effects on a known model. In the subsequent process, however, the classification is only between foraging and non-foraging classes, by considering the outputs of the cross-scale analysis.

Figure 1: Variation of classification performance (Accuracy and Kappa) according to different temporal window sizes used for calculation of movement parameters.
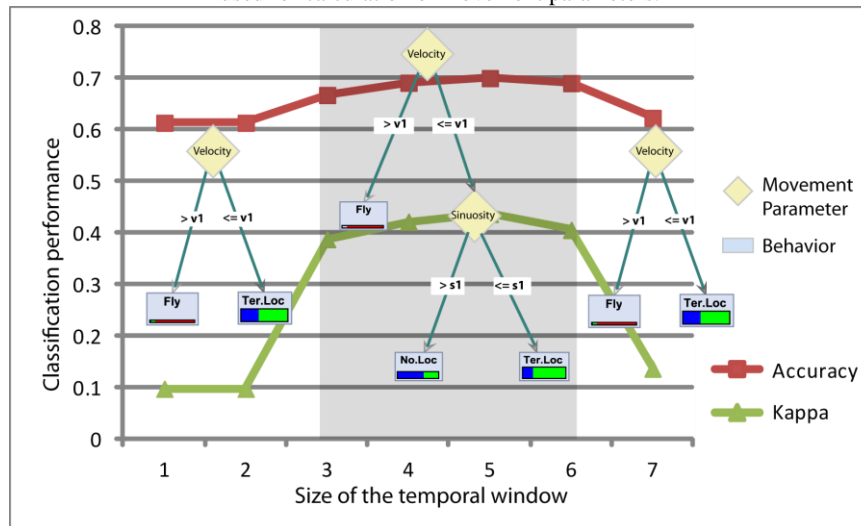

Interestingly, only after using a window size of 3 the role of sinuosity is starting to emerge in the structure of the decision tree (Figure 1). At the same time, for the window sizes of 3 to 6, higher classification accuracy and Kappa values were achieved. The tree structure for these window sizes was always the same, with velocity at the top, followed by sinuosity on the second level of the tree hierarchy (Figure 1). Since the window size of 5 scored relatively higher classification performance, it was selected as the window size at which sinuosity values can be reliably computed and considered as input features for the final classification.

4.2   Foraging versus non-foraging

In [18], a 5-class model has been calibrated that we are applying in this study; however we aggregate the output from 5 to 2 classes. First, since the fly class in the 5-class model can be easily distinguished from the stand, sit and foraging classes by using only the velocity parameter (Figure 2), the fly class is eliminated from the further analysis. The velocity values for the body care class are surprisingly high, which might be due to an error in the behavioral classification resulting from the accelerometer data. Nevertheless, since there were only two points labeled as body care, removing the fly class is still reasonable. Afterwards, all the non-foraging classes were aggregated and compared to the foraging class, resulting in a binary classification between a foraging class and a non-foraging class. Eliminating the fly class will help since there is a huge difference in the movement parameter values of the fly class and the rest of the classes, respectively, and if they were aggregated into a single class of non-foraging behaviors, it would have been difficult for the classifier to discriminate them. So, by first removing the fly class, only the sit, stand and body care classes will be aggregated into the non-foraging class. These behaviors share more similar movement characteristics.

In the end, there were 6486 fixes labeled as foraging and 4725 as non-foraging. Prior to applying the final classification, values of the selected attributes including distance traveled, velocity, sinuosity and MSSI are discretized into 3 bins, as it will help in improvement of the classification performance of the decision trees [5].

Figure 2: Boxplots of variation of velocity for five behavioral classes (Stand, Sit, Forage, Fly and Body Care).
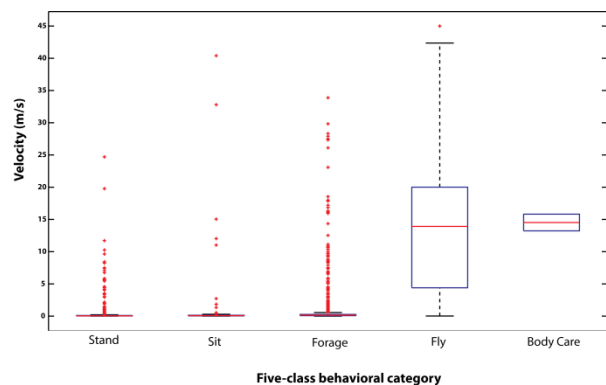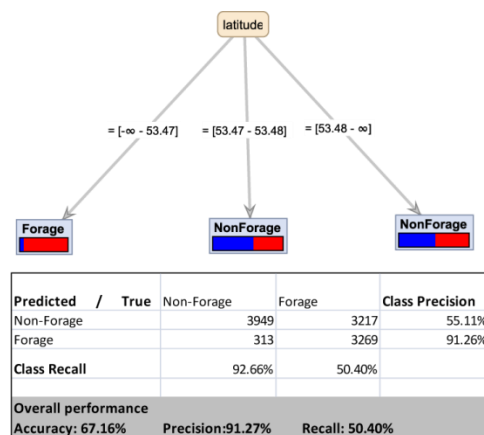

4.3   Importance of geographic context

To see whether knowledge about geographic context, represented by the geographic location of the birds, will help in identifying the behaviors, values of latitude and longitude of each fix were considered as input features in a classification tree. The resulting decision tree using only geographic location is shown in Figure 3. Apparently, latitude is a dominant variable in identifying behaviors, resulting in a

rather high classification accuracy of 67.16 %. However, very high classification precision (91.27 %) and at the same time very low recall values (50.40 %) does not indicate a robust performance. Nevertheless, this model will be considered as a baseline in order to compare with the following classification experiments, where values of movement parameters are integrated as well.

Subsequently, two separate decision trees based on the values of MSSI and sinuosity were developed (Figure 4). For each of these models, geographic location values were also integrated in order to make it possible to compare these to the baseline model developed in Figure 3. Additionally, since the importance of velocity and the distance traveled have been already emphasized, their values were also considered as input features in the classification model. Interestingly, both of the trees start with latitude at the top and then movement parameters are emerging at the lower levels (Figure 4).

Figure 3: The baseline decision tree for distinguishing foraging versus non-foraging developed based on location information, i.e. latitude and longitude. The confusion matrix is based on 10-fold cross-validation results.

Predicted / True	Non-Forage	Forage	Class Precision
Non-Forage	3949	3217	55.11%
Forage	313	3269	91.26%
Class Recall	92.66%	50.40%	
Overall performance			
Accuracy: 67.16%	Precision:91.27%	Recall: 50.40%	

5 Discussion

In the baseline classification model (Figure 3), the choice of latitude as a predictor variable in the decision tree can be understood from the east-west orientation of the Wadden island Schiermonnikoog, which provides the habitat of the studied individuals, located along the southern shore. The areas south of latitude 53.47° consist of mudflats with a short emersion time and high shellfish density. The area between 53.47° and 53.48° contains a combination of mudflats with long emersion time (which relates to a low shellfish density) and salt marshes. The area north of 53.48° contains salt marshes and meadow land. On the mudflats the Oystercatchers will feed on shellfish (mainly Baltic tellin − *Macoma baltica*) and ragworm (*Nereis diversicolor*). Conversely, on the saltmarsh and meadows they eat earthworms and insect larvae. The differences in habitat structure and prey types are reflected in different movement patterns.

As shown in Figure 4, the decision trees based on sinuosity and MSSI are not only improving the classification performance, but also give a more comprehensible overview of the importance of the movement features involved in combination with the underlying geographic location.

In the case of sinuosity, the leaves of the decision tree seem to be reasonable. Low values, indicating a smoother path, are labeled as foraging, whereas large values, indicative of a more complex path, are related to the non-foraging class (the path is more curved while the bird is sitting, standing or body caring due to GPS uncertainty). The values in the medium category are broken down again and distance values appear at the next level of the tree. The leaves at these levels are also sensible, as low and medium values of distance traveled are labeled as non-foraging and higher values as foraging. At the same time and as shown in Figure 1, it is worth noting that the usefulness of sinuosity is only revealed when the values are computed across different scales. In other words, if we had only used the sinuosity values computed at the original temporal rate, we could not have obtained the same results.

The resulting tree structure for MSSI is rather difficult to explain, but what looks interesting is the hierarchy in the structure of the tree (starting with window size 24x at the top and then 8x and 4x). Also, the tree is mostly dominated by foraging at the top (24x and 8x), while non-foraging only appears to be more dominant at the smallest scale (4x).
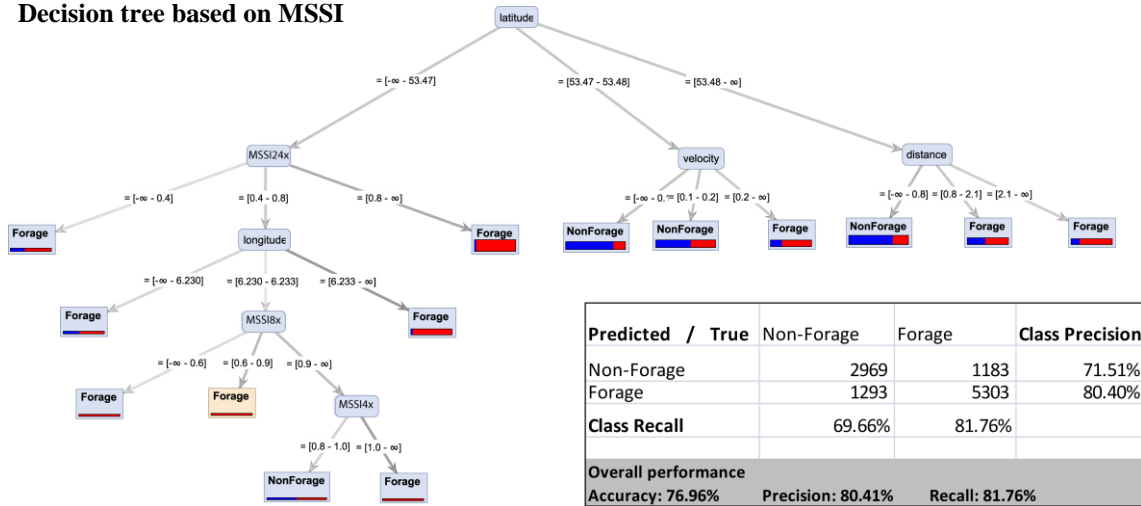
Resulting classification performances for the MSSI and sinuosity trees are comparable, with slightly better results for the sinuosity tree. As shown in the tables of Figure 4, overall accuracy and recall values are better for the sinuosity tree, whereas the MSSI tree results in a better precision value. Comparing to the baseline model developed based on geographic coordinates only (Figure 3), the classification performance is considerably better for the MSSI and sinuosity classification trees, leading to classifiers with an overall cross-validation accuracy of 0.78. This indicates a clear potential of parameters extracted from trajectories for the identification of movement-related animal behaviors.
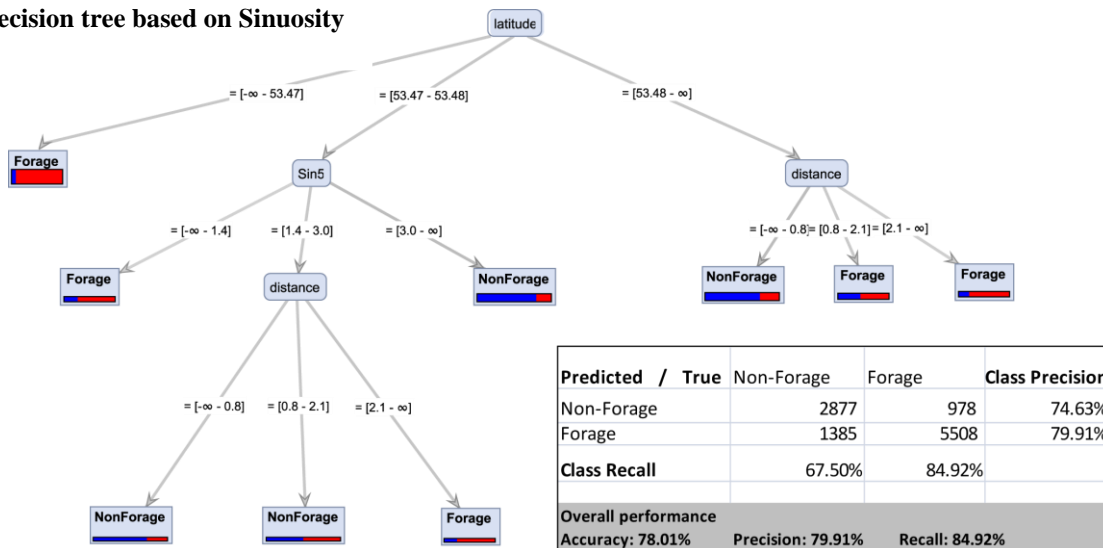
6 Conclusions

To our knowledge, most of the works based on movement features (e.g. sinuosity and MSSI) do not use a classification model and are rather descriptive. Sinuosity, for example, has only been applied to flying birds ([8, 22]) and not yet to wading birds that are foraging on the ground. Thus, a classification model based on trajectory features, as presented in this study, seems a useful contribution to exploit information from animal-borne sensors to further understand and model animal behavior. However, apart from sinuosity and MSSI, there are other features that have not been used yet, including e.g. first passage time, scale invariance and fractal dimension. Exploration of these features can be considered as part of future work. Furthermore, since using GPS trajectory data often stumbles on problems with accuracy, an assessment of the positional accuracy and its consequences for the distinction of behavioral types seems important in order to fully appraise the potential of the proposed approach.

Figure 4: Two developed decision trees based on the two employed movement features (together with velocity and distance traveled): Sinuosity calculated at window size of 5 (shown as sin5) and MSSI calculated at window sizes of 4, 8, 12, 16, 20 and 24. Depending on their importance, each of these features are emerging at different levels of the corresponding decision trees. Note that the confusion matrices related to each tree are based on 10-fold cross-validation results.

Decision tree based on MSSI

Predicted / True	Non-Forage	Forage	Class Precision
Non-Forage	2969	1183	71.51%
Forage	1293	5303	80.40%
Class Recall	69.66%	81.76%	
Overall performance			
Accuracy: 76.96%	Precision: 80.41%	Recall: 81.76%	

Decision tree based on Sinuosity

Predicted / True	Non-Forage	Forage	Class Precision
Non-Forage	2877	978	74.63%
Forage	1385	5508	79.91%
Class Recall	67.50%	84.92%	
Overall performance			
Accuracy: 78.01%	Precision: 79.91%	Recall: 84.92%	

Acknowledgments

References

[1] W. Bouten, E. W. Baaij, J. Shamoun-Baranes, and K. C. J. Camphuysen, "A flexible GPS tracking system for studying bird behaviour at multiple scales" *J Ornithol*, 571–580, 2013.

[2] L. Breiman, J. Friedman, C. J. Stone, and R. A. Olshen, Classification and regression trees. *CRC press*, 1984

[3] J. Cachat, A. Stewart, E. Utterback, P. Hart, S. Gaikwad, K. Wong, E. Kyzar, N. Wu, and A. V Kalueff, "Three-dimensional neurophenotyping of adult zebrafish behavior" *PloS one*, 6(3): e17597, 2011.

[4] S. Dodge, R. Weibel, and E. Forootan, "Revealing the physics of movement: Comparing the similarity of movement characteristics of different types of moving objects" *Computers, Environment and Urban Systems*, 33(6): 419–434, 2009

[5] J. Dougherty, R. Kohavi, and M. Sahami, "Supervised and Unsupervised Discretization of Continuous Features" *In Proceeding of 12th International Conference on Machine Learning, Lake Tahoe, CA, Morgan Kaufmann, Los Altos, CA*, 1995, pp. 194–202.

[6] B. J. Ens, M. Kersten, A. Brenninkmeijer, and J. B. Hulscher, "Territory quality, parental effort and reproductive success of oystercatchers (Haematopus ostralegus)" *Journal of Animal Ecology*, 61(3): 703–715, 1992.

[7] A. C. Gleiss, S. J. Jorgensen, N. Liebsch, J. E. Sala, B. Norman, G. C. Hays, F. Quintana, E. Grundy, C. Campagna, A. W. Trites, B. a Block, and R. P. Wilson, "Convergent evolution in locomotory patterns of flying and swimming animals" *Nature communications*, 2: 352–358, 2011.

[8] D. Grémillet, G. Dell'Omo, P. G. Ryan, G. Peters, Y. Ropert-Coudert, and S. J. Weeks, "Offshore diplomacy, or how seabirds mitigate intra-specific competition: a case study based on GPS tracking of Cape gannets from neighbouring colonies" *Marine Ecology Progress Series*, 268: 265–279, 2004.

[9] T. Guilford, J. Meade, J. Willis, R. A. Phillips, D. Boyle, S. Roberts, M. Collett, R. Freeman, and C. M. Perrins, "Migration and stopover in a small pelagic seabird , the Manx shearwater Puffinus puffinus: insights from machine learning" *Proceedings of Royal Society*, 276: 1215–1223, 2009.

[10] A. Gómez Laich, R. P. Wilson, F. Quintana, and E. L. c. Shepard, "Identification of imperial cormorant Phalacrocorax atriceps behaviour using accelerometers" *Endangered Species Research*, 10: 29–37, 2009.

[11] P. Laube and R. Purves, "How fast is a cow? Cross-Scale Analysis of Movement Data" *Transactions in GIS*, 15(3): 401–418, 2011.

[12] P. Martiskainen, M. Järvinen, J. Skön, J. Tiirikainen, M. Kolehmainen, and J. Mononen, "Cow behaviour pattern recognition using a three-dimensional accelerometer and support vector machines" *Applied Animal Behaviour Science*, 119: 32–38, 2009.

[13] Y. Mitani, R. D. Andrews, K. Sato, A. Kato, Y. Naito, and D. P. Costa, "Three-dimensional resting behaviour of northern elephant seals: drifting like a falling leaf" *Biology letters*, 6(2): 163–166, 2010.

[14] R. Nathan, O. Spiegel, S. Fortmann-Roe, R. Harel, M. Wikelski, and W. M. Getz, "Using tri-axial acceleration data to identify behavioral modes of free-ranging animals: general concepts and tools illustrated for griffon vultures" *The Journal of experimental biology*, 215: 986–996, 2012.

[15] L. Polansky, G. Wittemyer, P. C. Cross, C. J. Tambling, and W. M. Getz, "From moonlight to movement and synchronized randomness: Fourier and wavelet analyses of animal location time series data" *Ecology*, 91(5): 1506–1518, 2010.

[16] C. M. Postlethwaite, P. Brown, and T. E. Dennis, "A new multi-scale measure for analysing animal movement data" *Journal of theoretical biology*, 317: 175–185, 2012.

[17] Y. Ropert-Coudert, F. Daunt, A. Kato, P. G. Ryan, S. Lewis, K. Kobayashi, Y. Mori, D. Grémillet, and S. Wanless, "Underwater wingbeats extend depth and duration of plunge dives in northern gannets Morus bassanus" *Journal of Avian Biology*, 40(4): 380–387, 2009.

[18] J. Shamoun-Baranes, R. Bom, E. E. van Loon, B. J. Ens, K. Oosterbeek, and W. Bouten. "From Sensor Data to Animal Behaviour: An Oystercatcher Example" *PloS one*, 7(5): e37997, 2012.

[19] J. Shamoun-Baranes, E. E. van Loon, R. S. Purves, B. Speckmann, D. Weiskopf, and C. J. Camphuysen, "Analysis and visualization of animal movement" *Biology letters*, 8(1): 6–9, 2012.

[20] A. Thiebault and Y. Tremblay, "Splitting animal trajectories into fine-scale behaviorally consistent movement units: breaking points relate to external stimuli in a foraging seabird" *Behavioral Ecology and Sociobiology*, 67(6): 1013–1026, 2013.

[21] S. M. Tomkiewicz, M. R. Fuller, J. G. Kie and K. K. Bates. "Global positioning system and associated technologies in animal behaviour and ecological research" *The Royal Society*, 365: 2163–2176, 2010.

[22] H. Weimerskirch, F. Bonadonna, F. Bailleul, G. Mabille, G. Dell'Omo, and H.-P. Lipp, "GPS tracking of foraging albatrosses" *Science*, 295: 1259–1259, 2002.

[23] G. Wittemyer, L. Polansky, I. Douglas-hamilton, and W. M. Getz, "Disentangling the effects of forage , social rank , and risk on movement autocorrelation of elephants using" *Proceedings of the National Academy of Sciences*, 105(49): 19108–19113, 2008.

[24] Z. Yan, Semantic Trajectories : Computing and Understanding Mobility Data, *PhD Thesis*. 2011.

[25] C. B. Zavalaga, G. Dell'Omo, P. Becciu, and K. Yoda, "Patterns of GPS tracks suggest nocturnal foraging by incubating Peruvian pelicans (Pelecanus thagus)" *PloS one*, 6(5): e19966, 2011.