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A method to detect inactive periods in animal movement using density-based clustering

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A B S T R A C T

In this paper, we propose a method to find inactive periods of a trajectory and employ it to livestock tracking.

In contrast to the existing methods to find inactive periods in the domain of animal movement studies, the proposed method estimates inactive periods based on the position recordings only, without involving information from activity sensors or field observations. The only parameter that the proposed method requires is the minimum duration of inactivity. Inactivity means being stationary or having limited variation in position. The results have been verified by applying the method to a dataset where activity sensor recordings are also available.

1. Introduction

Recent developments in location-aware technologies (including GNSS "Global Navigation System Satellite" (e.g. (Awange, 2012)), RFID 'Radio Frequency Identification' (e.g. (Kritzler, Raubal, & Krüger, 2007)), and cell phone tracking (e.g. (Abedi, Bhaskar, & Chung, 2014; Versichele, Neutens, Delafontaine, & Van de Weghe, 2012)) have significantly increased their use in data collection for moving object applications. Analyses and methods for extracting useful information from these increasingly large dataset have lagged behind the technology for generating them (Long & Nelson, 2013).

Wearable tracking collars have simplified monitoring of animal locations for many research projects in within ecology (Cagnacci, Boitani, Powell, & Boyce, 2010) and geography (Laube & Purves, 2011; Stewart, Nelson, Wulder, Nielsen, & Stenhouse, 2012; Technitis, Othman, Safi, & Weibel, 2015). Tracking an animal using tracking collars results in a trajectory which is a sequence of ordered records in time depicting the movement of the object (Gudmundsson, Laube, & Wolle, 2011; Long & Nelson, 2013). However, the so-called raw trajectory lacks semantic interpretation (Bogorny, Renso, Aquino, Lucca Siqueira, & Alvares, 2014). According to Spaccapietra et al. (2008), a raw trajectory may semantically be segmented into 'move' and 'stop' parts, an event-based perspective (Hornsby & Cole, 2007). In the conceptual framework of an application, the spatial range of the trajectory for each 'stop' part is a single point (Spaccapietra et al., 2008). In animal movement studies, 'stop' and 'move' parts of the raw trajectory correspond to inactive periods (e.g., resting bouts) and active periods (e.g., foraging bouts) (Frair et al., 2010; Schwager, Anderson, Butler, & Rus, 2007).

Segmenting animal trajectories by detecting inactive periods in the presence of positioning error is the main goal of this paper. Positioning error is still considered an important concern in different applications, including animal movement studies ((Ganskopp & Johnson, 2007; Hurford, 2009; Jerde & Visscher, 2005), to name but a few). When an animal sleeps or lies down and rests at one location for a period, the collected positions can be misplaced, due to positioning error, complicating the detection of inactivity. Undetected periods of inactivity may lead to biological misinterpretation (Pepin, Adrados, Mann, & Janeau, 2004), e.g. degrade the estimation of spatial habitat use pattern or the evaluation of energetic requirement of animals.

In this paper, we investigate how well active and inactive periods of animals can be distinguished relying only on positions from non-differentially corrected GPS 'Global Positioning System' recordings. Positioning error is generally not available for the individual recordings, so we suggest a method for estimating the positioning error for the detected inactive periods. Due to the lack

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of empirical evidence (e.g., field observations) to validate the results, findings of the study are verified by utilizing available activity sensor data. A simulation is also conducted to evaluate the percentage of the inactive periods detected correctly by the proposed method.

The paper is structured as follows. In Section 2, we provide a brief literature review on methods for extracting inactive periods of GPS-tracked animals. In Section 3 (Methodology), a detailed description of the proposed method is given. In Section 4 (Case study), an explanation of our equipment to track domestic sheep on an alpine range is given. In Section 5 (Result), we apply the proposed method to our dataset and evaluate the outcomes based on the available activity sensor recordings. In Section 6 (Validation), we use a Random Walk model and a Correlated Random Walk model to simulate animal paths and evaluate what percentage of the simulated inactive periods that can be detected by the proposed algorithm.

2. Background and related works

An *Inactive Period* (*IP*) is defined as a state where the animal is stationary or has limited variation in geographic location. With error-free location data, defining a threshold value for the variation in geographic location would be sufficient to detect *IPs*. However, with errors in the location data, more sophisticated approaches are required to identify *IPs*.

In the literature of animal movement studies, inactive periods have been identified by combining activity sensor values and movement variables based on GPS recordings (Frair et al., 2005, 2010; Ganskopp & Johnson, 2007; Pepin et al., 2004; Schwager et al., 2007; Ungar et al., 2005; Van Moorter, Visscher, Jerde, Frair, & Merrill, 2010). Inactive periods (bedded, standing) and active states (feeding, moving) of animals have been identified using predictive models by including information from various sensors along with field observations (Body, Weladji, & Holand, 2012; Grunewalder et al., 2012).

Gervasi, Brunberg, & Swenson (2006)) tested an individual-based method to discriminate active and inactive periods for brown bears using dual-axis motion sensors mounted on GPS (Global Positioning Systems) collars. The motion sensors mounted on the collars "separately measure the true acceleration of the collar in 2 orthogonal directions 6–8 times per second". The acceleration values acquired between 2 consecutive recordings were averaged, ranging from 0 to 255, and assigned to each direction. They found that the frequency distribution of motion sensor values was bimodal, and they identified a separation point and considered all activity values lower than the separation point as inactive.

Ganskopp & Johnson (2007) tried to select an activity sensor value threshold between active and inactive periods based on left-right sensor values of GPS collars worn by cattle. The activity sensor values, ranging from 0 to 255, were acquired at 5-min intervals. They visually identified the first point of inflection of the cumulative frequency curve of increasing activity values as a break point separating inactive and active periods. They found out that they needed to combine the activity value and a minimum distance threshold to filter out inactive periods from active periods.

Schwager et al. (2007) used the k-mean classification algorithm to categorize tracking data from cows into two groups corresponding to active and inactive periods. They used position and head angle data to demonstrate how the algorithm can be employed in a behavioral study.

Adrados, Baltzinger, Janeau, & Pepin (2008) proposed an individual-based relative method using the count provided by a GPS collar activity sensor to separate active from inactive periods. A dataset from free-ranging red deer (Cervus elaphus) was used to pinpoint locations where animals were inactive versus active. For each individual and day of measurement, the mean activity during a 24-hr period was defined as the referential slope (a_0). Then the slope of each pair of successive activity values (a) was compared with (a_0). The animal was considered inactive during the time interval under consideration if $a < a_0$.

To our knowledge, most prior studies in this area have been conducted based on the existence of activity sensor values and field observations. With only location data available, it is a challenge to discriminate between active and inactive periods. Due to the lack of sufficiently fine resolution of activity sensor values and field observations in our data (see the case study section for details about the current dataset), we were interested in developing methods that only requires location data.

In the study of movement data, which is the forefront of Geographic information science research (Alvares et al., 2007; Andrienko et al., 2013; Long & Nelson, 2013; Palma, Bogorny, Kuijpers, & Alvares, 2008; Tran, Nguyen, Do, & Yan, 2011; Zimmermann, Kirste, & Spiliopoulou, 2009), the term 'stop' is used as a synonym for an inactive period (*IP*). Many analytical approaches in this area rely on geometrical properties and movement parameters of the trajectory, such as distance, duration and speed. The Euclidean distances between recordings in a fixed time window could be used to detect *IPs*, but identifying appropriate values for the Euclidean distances and time window length is challenging. In addition, such an approach is sensitive to outliers. Another approach could be to use the average Euclidean distance in a time window (Laube & Purves, 2011), but that reduces the sensitivity to the spatial distribution of the recordings.

Andrienko et al. (2013) classify stop detection methods based on movement parameters such as speed (Palma et al., 2008; Yan, Parent, Spaccapietra, & Chakraborty, 2010), distance (Phithakkitnukoon, Horanont, Di Lorenzo, Shibasaki, & Ratti, 2010), speed and duration (Zimmermann et al., 2009), speed and distance (Buard, 2011) and direction (Rocha et al., 2010). Among the different approaches to detect stops, density based clustering methods has attracted the attention of many researchers (Palma et al., 2008; Tran et al., 2011; Zimmermann et al., 2009). They develop adapted versions of 'Density-Based Spatial Clustering of Applications with Noise' (DBSCAN) (Ester et al., 1996). Based on a given set of points, DBSCAN cluster points that are located closely together in space. Our DBSCAN based method is original in the sense that it takes particular advantage of the trajectory aspect in our recordings (dataset) and detect *IPs* using a combined time-space distance measure.

Birant & Kut (2007) presented a spatio-temporal clustering method based on DBSCAN named ST-DBSCAN. This method has the ability to discover clusters according to non-spatial, spatial and temporal values of objects while DBSCAN finds clusters according to only the spatial values of objects. However, ST-DBSCAN handles spatiotemporal data stored as temporal slices, and it is not suitable for trajectory data. Spatial and temporal distances are defined separately, and the similarity of objects are defined by a conjunction of the two metrics.

Zimmermann et al. (2009) propose an interactive density-based clustering algorithm based on OPTICS (Ankerst, Breunig, Kriegel, & Sander, 1999) to discover stops in a trajectory. The density is defined based on the spatial and temporal properties of the trajectory and the potential stops are extracted interactively, which requires some domain knowledge. The advantage of the method is its applicability for trajectories of different transportation modes, so-called heterogeneous trajectories.

More relevant to our idea is the approach (CB-SMoT) of Palma et al. (Palma et al., 2008) suggesting a spatio-temporal clustering method for finding interesting places on the trajectory of a moving