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A feature extraction based trajectory segmentation approach based on multiple movement parameters

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Abstract

Analyzing the trajectories of movements among moving objects is of interest in many fields to understand the dynamics and behavior of those objects. In this paper, a cluster-centric trajectory segmentation approach is proposed to reveal and visualize segments of trajectories among moving objects. Characteristics such as position, direction, and speed of moving objects (called movement parameters) are considered for this purpose. First, profiles generated for different movement parameters are divided into several portions using sliding windows of different length. Next, changes with respect to each particular movement parameter profile in the sliding windows are extracted as features. Finally, by clustering the extracted features, subsequences of trajectories with similar movement characteristics are detected. Some cluster-validity indices were used to find the (near) optimal number of clusters. The performance of the proposed segmentation technique is evaluated through a trajectory clustering as well as a movement pattern detection case study over some real-word datasets.

Keywords: trajectory segmentation; trajectory clustering; movement parameter; sliding window

1. Introduction

The advances in location-aware technologies such as GPS and GSM networks and also the recent development of computer vision based motion detection techniques have led to a considerable increase of Moving Objects Databases. The availability of massive mobility trajectory data has raised increased interest in trajectory data mining and knowledge discovery. Analyzing trajectory datasets and understanding the dynamic behavior of moving objects has many applications in different sciences. In mobility and transportation, processing and analyzing the human urban mobility data can be used in designing location-based-services (LBS). Moreover, analyzing the trajectories in an urban movement network is applied for traffic management, e.g. in order to detect traffic jams. Marketing is another field in which analyzing

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the trajectory of moving objects is helpful to improve business outcomes. Identifying the trajectories of customer movements in supermarkets provides sale managers with useful information for product line design. In Sports Scene Analysis e.g. soccer, processing a player's movement patterns helps coaches to learn about the opponent team's behaviors and strategies (Laube et al., 2005 and Izakian et al., 2016).

In the physical world, moving objects are classified into two categories. First, the objects which preserve a constant shape when moving (e.g. human, vehicle, animal) and are often represented as point elements; second, objects that change their shapes over time and are known as processes (e.g. bushfire, oil spill) (Sharif and Alesheikh, 2017). Since the interactions in points are simple and points are more capable of saving the moving object's properties, we focus on analyzing moving point objects in this research.

Often the number of observations in trajectories (in other words the size of trajectories) is large. As a result it is essential to use techniques to reduce the trajectories' complexity while maintaining significant movement features. Trajectory segmentation is a great tool to reduce trajectories' dimensionality, and dividing them into a small number of meaningful homogeneous moving patterns.

The movement characteristics such as speed, acceleration, latitude/longitude/altitude, heading and so on are similar in some senses in each segment. In moving objects trajectory studies, considering movement parameters such as speed, acceleration, direction, etc. along with information related to the position of objects results in a better understanding of moving patterns.

Data collected by GPS usually contain a significant amount of noise, since the segmentation process is sensitive to noise and segmenting noisy data leads to increasing the number of segments, or splitting data in unnecessary locations. Therefore, using segmentation methods with a global view of datasets is more robust against noise and can be helpful in reducing the noise effects and capturing the most important characteristics of a stream.

Segmentation studies may be classified into two categories. In the first group, segmentation methods are based on the shape of the trajectory. In this case, segmentation is performed with regard to the geometric structure of the trajectory such as straightness or sinuosity and so on. In the second group of studies, trajectories are split into segments with similar values of derived movement parameters such as speed, acceleration, heading, etc. and as a result sub-trajectories expressing similar movement parameters are discovered in these methods (Laube et al., 2005).

A review of the literature relevant to research on movement similarity analysis shows that the applied similarity analysis techniques in most cases focus on the geometric structure of movement trajectory, while only a few consider the variations of movement parameters. In many applications, detecting objects with similar movement patterns may not be possible by considering only the spatial similarity. For example, trajectories of various vehicles with different speeds that move on the same route are similar in terms of geometric shape, while with taking in to account the variation of movement parameters like speed, the vehicles that follow different patterns over time can be discovered (Dodge et al., 2012).

The main contribution of this research is presenting a novel trajectory segmentation technique which results in a compressed representation of trajectories according to the variability of their movement parameters over time. The proposed technique has two main characteristics, on the one hand, the simultaneous involvement of various movement parameters in the segmentation process and on the other hand, the use of variable size sliding window.

In Section 2 we present a brief literature review. In Section 3 we review some necessary background materials to this paper. Section 4 briefly describes the proposed method. In

Section 5 we evaluate the performance of the proposed methodology in two applications including trajectory clustering and movement pattern detection over some real datasets. In Section 6 we have discussed the proposed method and Finally Section 7 concludes this study.

2. Related work

In this section we first review some researches which defined trajectory segmentation process as the procedure of converting trajectories into a symbolic representation.

Lin et al. (2003) presented a novel symbolic representation method for time series data. Assuming that normalized time series data usually have a Gaussian distribution, they determined a number of breakpoints that produce equal-sized areas under the Gaussian curve. Next, the data is transformed into a Piecewise Aggregate Approximation (PAA) representation. By assigning a unique symbol to each area, the PAA coefficients mapped into SAX symbols. In order to evaluate the new symbolic dimension reduction technique, the authors illustrated the usefulness of their symbolic representation method on various fields of data mining, including clustering, classification, query by content, anomaly detection, motif discovery, and visualization.

Chen et al. (2004) proposed a new dimension reduction method for Moving Object Trajectories called MPS. MPS is a symbolic representation of a trajectory based on two parameters including movement direction, and distance ratio information, which derived from the positions of moving objects in the trajectory. The two-dimensional space (movement direction, distance ratio) was equally divided into sub regions and a distinct symbol assigned to each sub region. According to their paper, by dividing each axis (corresponding to a specified movement parameter) into eight parts, 64 sub regions were achieved. For the method evaluation they implemented their method on two labeled data and reported the results.

Dodge et al. (2012) proposed a novel method for finding similar trajectories, using trajectory segmentation based on movement parameters such as speed, acceleration etc. At the first step, the profile of a specified movement parameter is generated, and then the profile points regarding the variations in sinuosity and deviation from the median line are classified into distinct classes according to a user-defined threshold. In this paper, a modified version of edit distance, called Normalized Weighted Edit Distance (NWED) is introduced as a similarity measure between different sequences. The performance of their approach is assessed in two case studies using real movement datasets from two different application domains, namely, North Atlantic Hurricane trajectories and the GPS tracks of couriers in London.

In the symbolic representation methods mentioned above, the usual procedure involves partitioning the range of movement parameters into several parts and representing each value in a particular range with a symbol assigned to the corresponding class. By considering more movement parameters in the segmentation process (e.g. increasing the number of movement parameters), the number of classes and as a result the number of symbols will be increased significantly and the method loses its efficiency.

Recently some trajectory segmentation approaches have been introduced to identify animal behavioral states. Among these methods some techniques have been focused on behavioral change points while in some others recognizing both behavioral change points and behavioral modes are taken into consideration.

Gurarie et al. (2009) modeled movement data as a subsampling of continuous stochastic processes, and proposed a likelihood-based method to analyze the behavioral change point (BCPA) to identify the significant structural changes.

Thiebault & Tremblay (2013) proposed a segmentation method based on the consistency of two parameters speed and direction to recognize behavioral change points. In this method the movement between sequence points was shown with a vector of speed and direction for distinguishing changes in animals' behavioral mode.

Zhang et al. (2015) used a three-step framework, including BCPA, hierarchical multivariate cluster analysis, and k-means clustering to extract the behavioral states in real penguins' tracks. In their study BCPA with the fix size windows is applied to recognize behavior change points. Hierarchical multivariate cluster analysis is employed to determine the number of clusters and k-mean clustering is used to cluster the segments based on combinations of speed and turning angle.

Van toor et al. (2016) presented a method named niche segmentation algorithm that uses the changes in the environmental correlates of a trajectory to partition animal movement trajectories into segments of higher ecological coherence. This method is a new class of segmentation algorithms and it's based on changes of habitat use, instead of movement geometry. The experimental results indicated that environmentally informed trajectory segmentation can provide useful information about animal behavior along movement.

Gurarie et al. (2016) categorized behavioral movement analysis methods into four groups: metric based, classification and segmentation, phenomenological time series analysis, and mechanistic movement modeling. Four methods from the four categories including first passage time (FPT), Bayesian partitioning of Markov models (BPMM), behavioral change point analysis (BCPA) and a fitted multistate random walk (MRW) are implemented and compared to three simulated tracks and two animal trajectories comprising a sea lamprey tracked for 12 h and a wolf tracked for 1 year.

Teimouri et al. (2018) introduced a methodology to extract animal movement behavior based on high-frequency GPS data. By production of speed and turning angle vectors and using BCPA method with fixed size window they partitioned movement trajectory into segments, which are homogeneous in terms of their movement parameters. They used hierarchical clustering for grouping the obtained segments according to their estimated movement parameters.

Damiani et al. (2018) introduced a clustering-based segmentation method named SeqScan for partitioning trajectories into consecutive sub-sequences based on spatial density criteria. To deal with the noise, they presented a model based on two different types of noise including local noise and transition noise. In their study, the local noise and the transition noise are defined as the temporary absence from a residence and the departure towards a next residence respectively. They evaluated the performance of SeqScan using the ground truth which was including a set of animal trajectories.

Ahearn and dodge (2018) introduced a new approach to segment the movement trajectories at multiple scales. They stated that to behavior identification in a complex trajectory it is important to use a segmentation method that captures (takes) different frequency ranges. Their proposed method has the ability of detecting movement patterns at multiple temporal frequencies. They tested their method on two sets of simulated data and GPS tracking data and evaluated the ability of the method in extracting movement behaviors.

Chakravarty et al. (2019) introduced a framework for identification of animal behavior pattern using accelerometers. They presented a hybrid model by combining first, movement biomechanics features which characterize movement dynamics and second, machine learning hierarchical classification which was employed at each node to find thresholds with the goal of separating different behaviors. The authors implemented their approach on Kalahari Meerkats data to detect four different behavior classes including vigilance, resting, foraging and running.

Among trajectory segmentation techniques there are approaches that apply wavelet transform to infer behavioral states from movement trajectories.

Sur et al. (2014) introduced a trajectory segmentation approach based on discrete wavelet transform. Supposing that the Z-scores of detail coefficients at a certain wavelet decomposition level follow a normal distribution, they used the detail sub-bands to detect individual behavioral change points.

Soleymani et al. (2017) proposed a novel segmentation method based on the discrete wavelet transform (DWT). In this method the movement parameter profile is decomposed into low-frequency approximation and high-frequency detail sub-bands. They used the Approximation sub-bands in order to recognize the general structure in the data detail. Sub-bands are employed to detect fine scale behaviors. In order to evaluate the ability of the proposed method to identify behavioral models in simulated trajectories, they compared it to three state-of-the-art methods. Furthermore, their method is validated using an annotated dataset of turkey vultures (*Cathartes aura*). By considering speed as the relevant MP signal for wavelet analysis, they indicated the ability of their proposed method in extracting migratory vs. non-migratory patterns.

In Table 1 we compare the trajectory segmentation methods which are mentioned in this section.

Table 1: Comparing trajectory segmentation approaches

Method	Suitable for long noisy data	Windows size	Number of parameters involved	Application for validation
Lin et al. (2003)	No	Fixed size	One parameter	Clustering
Chen et al. (2004)	No	Fixed size	Two parameters (speed and turning angle)	Clustering
Gurarie et al. (2009)	Yes	Fixed size	Two parameters (speed and turning angle)	Deriving animal movement behaviors
Dodge et al. (2012)	No	Fixed size	One parameter (speed or turning angle)	Clustering
Thiebault & Tremblay (2013)	Yes	Fixed size	Two parameters (speed and turning angle)	Deriving animal movement behaviors
Sur et al. (2014)	No	-	Two parameters (step length and residence time data)	Deriving animal movement behaviors
Zhang et al. (2015)	Yes	Fixed size	Two parameters (speed combining turning angle)	Deriving animal movement behaviors
Van toor et al. (2016)	Yes	Fixed size	temporal distance	Deriving animal movement behaviors
Soleymani et al. (2017)	Yes	-	One parameter (speed)	Deriving animal movement behaviors
Teimouri et al. (2018)	No	Fixed size	Two parameters (speed and turning angle)	Deriving animal movement behaviors
Damiani et al. (2018)	Yes	-	One parameter (position)	Deriving animal movement behaviors

Ahearn and Dodge (2018)	No	-	One parameter (speed)	Deriving animal movement behaviors
Chakravarty et al. (2019)	Yes	Fixed size	One parameter (acceleration)	Deriving animal movement behaviors
Proposed method	Yes	Variable size	numerous parameters	<ul style="list-style-type: none"> • Clustering • Deriving animal movement behaviors

Table 1 points to some limitations of current trajectory segmentation techniques, which the method proposed in this paper (Section 4) seeks to address:

- All methods in this table rely on one or maximum two given movement parameters to segment trajectories, while our proposed approach can receive numerous movement parameters as inputs. In other words, the presented approach can potentially investigate different movement profiles simultaneously and extract any important information existing in each profile. Thus, in contrast to other methods, our method is not limited to the challenge of choosing a particular movement parameter for the segmentation process.
- Because of the unpredictable variability of movement data, the fixed size window is not a good choice to divide a trajectory. Using a variable-size sliding window technique to produce a set of sub-profiles is another advantage of our proposed method.
- The proposed technique in this study can be applied for trajectory segmentation in different applications, while some methods of Table 1 were introduced only for a specific application.
- Dealing with long noisy trajectories is another major advantage of our method, which has not been considered in some segmentation methods.

3. Fuzzy C-Means and Discrete Wavelet Transform

In this section we review Fuzzy C-Means (FCM) and the Discrete Wavelet Transform (DWT), two popular techniques for data clustering and noise reduction, respectively, as background for the presentation of our proposed segmentation method in Section 4.

3.1. FCM clustering algorithm

Clustering is a process of partitioning data into meaningful groups of similar objects. Fuzzy C-Means is of the most commonly used fuzzy clustering method based on the idea of optimizing an objective function (Bezdek, 1981). In this technique each data point can belong to more than one cluster. FCM assigns a membership value to each data point for each cluster according to the distance between the data point and the cluster center in the feature space.

FCM clusters n objects $r_1, r_2, \dots, r_n$ into c groups through the minimization of the following objective function (Izakian et al., 2015).

$$J = \sum_{i=1}^c \sum_{k=1}^n u_{ik}^m d^2(v_i, r_k) \quad (1)$$

In this method a set of c cluster centers $v_1, v_2, \dots, v_c$ and a partition matrix $U=[u_{ik}]$, $i=1,2,\dots,c$, $k=1,2,\dots,n$ describing the membership degrees of each object to each cluster, are calculated with the following properties:

$$u_{ik} \in [0,1], \sum u_{ik} = 1 \forall k, \text{ and } 0 < \sum u_{ik} < n \forall i \quad (2)$$

The partition matrix can be calculated as follows:

$$u_{ik} = \frac{1}{\sum_{j=1}^c \left(\frac{d(v_i, r_k)}{d(v_j, r_k)} \right)^{2/(m-1)}} \quad (3)$$

By considering Euclidean distance function in (1), cluster centers are calculated using equation (4).

$$v_i = \frac{\sum u_{ik}^m r_k}{\sum u_{ik}^m} \quad (4)$$

The process is iterative and the cluster centers and partition matrix are generated in a number of iterations to minimize the objective function expressed in (1).

In this study FCM is used to group similar parts with similar behavior in terms of a number of features of trajectory data.

Clustering techniques usually have an acceptable performance in dealing with “clean” data. In cases where these techniques face real-world applications where patterns are usually noisy, the achieved outcomes are not always reliable (Chen et al., 2019). In other words, the existence of noise in the data can affect the clustering results and their interpretation. In the following section the discrete wavelet transform, a powerful technique for noise reduction, will be reviewed.

3.2. Discrete Wavelet Transform

The noise removal techniques generally are grouped into two categories including removing noise in the original signal domain (e.g. time or space) and removing noise in the transform domain (e.g. Fourier or Wavelet Transform). For stationary signals which have no change in the mean and variance of the signal over a period of time, the traditional Fourier Transform (FT) is an appropriate method, while for non-stationary signals where the time-frequency representation of the signal is needed (like movement time series where, behavior of the moving object changes along a trajectory), Wavelet Transform is a powerful tool to remove noise (Bogges & Narcowich 2009). Moreover Fourier Transform only transforms a signal in a frequency domain and no information on time of occurrence of frequencies is captured, while in the wavelet transform both frequency and time are considered in signal decomposition. Since we are dealing with trajectory data in this study, wavelet transform has been considered to remove noise from long noisy trajectories.

Wavelet transform is a signal decomposition technique which decomposes a signal into multiple lower resolution levels by controlling the scaling and shifting factors of a single wavelet function called the mother wavelet. There are two main types of wavelet transforms, the continuous wavelet transform (CWT) and the discrete wavelet transform (DWT). In DWT the shifting and scaling of the mother wavelet function is based on powers of 2 so-called dyadic scales and positions whereas the CWT can operate at every scale. Using Discrete wavelet Transform (DWT) the time series is converted into two types of coefficient by passing the original movement time series through low-pass and high-pass filters and this results in

approximation coefficients vector (cA) and detail coefficients (cD) vector. Approximation coefficients or the low-frequency contents maintain the general structure of the time series and give the signal its identity. On the other hand, the high-frequency content, illustrates time series details. It is possible to reconstruct the original signal from the coefficients of the approximations and details through an inverse discrete wavelet transform process. If in the reconstruction process the high-frequency content is neglected and instead of combining approximation coefficients with the detail coefficients, we feed in a vector of zeros in place of the details, the smoothed version of original signal will be achieved (Soleymani et al., 2017).

4. Proposed Method

Figure 1 illustrates the overall flow of the proposed segmentation technique. A step by step explanation of our proposed approach is presented in the following.

Figure 1: Methodology

Generating profiles of independent movement parameters:

In real-world phenomena, the movement parameters of most moving objects such as direction of movement, speed, acceleration, etc. change over time, and the evolution of their movement parameters can be illustrated through a profile (Dodge et al., 2009, Dodge et al., 2012). Analyzing movement parameter profiles reveals meaningful information about the object's movement behavior at different time steps.

At the first step of the proposed method, the profiles of movement parameters such as position, speed, turning angle are generated from the trajectory of movement.

In Figure (2) the normalized profiles of position, speed and turning angle are shown for a moving trajectory. Figure 1a shows the trajectory of a moving object and Figures 1b, 1c, and 1d shows the profile of position, speed, and turning angles. The profile of position shows the position of the feature which is computed using X and Y coordinates each time. To create the speed profile of a feature such as speed the distance traveled by the moving object between two different points, should be divided by the total time it took for the moving object to cover the distance. To achieve the turning angle profile, the movement direction changes should be computed in various times.

Figure 2: Movement parameter profiles

Wavelet transform for extracting general pattern:

At the second step, noise was removed from the generated movement profiles. Although there are many techniques such as Discrete Fourier Transform (Faloutsos et al., 1994), DCT (Jain, 1989), Moving Average techniques (Korn et al., 1997) and etc. for noise reduction in time series datasets, in this study we considered DWT. The reason was that trajectory data are usually non-stationary signals with behavior changes over time (Edit paragraph). Moreover, despite using the traditional Fourier method where only the frequency of the signal is captured, the wavelet transform captures both frequency and time.

In noise removal process using DWT, the generated profiles were decomposed by DWT and then by omitting the small coefficients (the high-frequency content) and setting them to zero, the reconstructed version of profiles (signals with removed noise) was achieved using the inverse discrete wavelet transform (IDWT).

Profile decomposition using sliding windows:

The next step is generating a number of sub-profiles by moving a sliding window over the generated noise-reduced profiles. Generally, a sliding window moves thorough a signal (here a profile) and generates a number of subsequences. The main goal of generating those sub-profiles is looking into movement parameters at each part of the original trajectory locally and capture any changes which has occurred in trajectory behavior.

The goal of this study is moving object behavior analysis based on different movement parameters (speed, acceleration, turning angle and so on) at each part of the original trajectory. For this purpose a sliding window moves over various profiles (e.g. speed and turning angle) simultaneously, and generates a number of sub-profiles, i.e., speed sub-profile and turning angle sub-profile in each slide. It is important that the sub-profiles are generated in such a way that the profile slope in each sub-profile is homogenous. The slope of movement parameter profile or in other words, the rates of change of movement parameters is an appropriate choice to understand the crucial features of the movement process. The high probability of identifying the events existing in a trajectory by investigating trajectories' rate of change of movement parameters led us to use the slope of movement parameter profiles for defining feature within the proposed method. (Lauble et al., 2007 & Zheng et al., 2008)

Generally, there are two types of sliding windows for splitting time series and trajectory data. In the first type, the time series is segmented into equal-length subsequences using a fixed-size sliding window. In this case, the end-user might select a fixed-size sliding window and movement length, according to some available patterns in time series such as seasonality and the application purpose. Although implementing a fixed-size sliding window is an easy and straight way of splitting time series data into smaller subsequences, it might impact the performance of the overall algorithm. Selecting a small sliding window will increase both space and computation time for query execution and using long windows might hide available

information inside generated subsequences. The second type is to have variable-length sliding windows based on the characteristics of the trajectories in each part (Egiazarian et al., 2000). In reality, moving objects might show more or less dynamics in various time steps which indicates the need for variable-size sliding windows for trajectory data.

Inspired by the SAX representation technique proposed by Lin et al. (2003), in our method we use a variable-size sliding window technique to generate a set of sub-profiles according to their slope. Moreover, to prevent information loss in the split points some small overlap between any two consequent sub-profiles has been considered.

In the SAX representation technique, assuming that a normalized signal has a highly Gaussian distribution, there is a sorted list of numbers which splits the area under a Gaussian curve into an arbitrary number of equi-probable regions. These numbers can be derived by looking them up in a statistical table (Table 2) (Lin et al., 2003). In Table 2, a is the number of equi-probable regions divided by breakpoints and β shows the breakpoint.

Table 2: Statistical table including breakpoints that divide a Gaussian distribution into an arbitrary number of equi-probable regions (Lin et al., 2003)

a β	3	4	5	6	7	8	9	10
β_1	-0.43	-0.67	-0.84	-0.97	-1.07	-1.15	-1.22	-1.28
β_2	0.43	0	-0.25	-0.43	-0.57	-0.67	-0.76	-0.84
β_3	-	0.67	0.25	0	-0.18	-0.32	-0.43	-0.52
β_4	-	-	0.84	0.43	0.18	0	0.14	-0.25
β_5	-	-	-	0.97	0.57	0.32	0.14	0
β_6	-	-	-	-	1.07	0.67	0.43	0.25
β_7	-	-	-	-	-	1.15	0.76	0.52
β_8	-	-	-	-	-	-	1.22	0.84
β_9	-	-	-	-	-	-	-	1.28

In this paper, we used these breakpoints (according to Table 2) to generate subsequences with different lengths. Since we are looking for the windows with slight slope changes, for each movement parameter profile the slope chart will be extracted. The slope chart is a chart which at each time gives us the slope of the movement parameter profile (Figure 3-b). Then, the breakpoints split the slope chart (that has a highly Gaussian distribution) into sub-charts. The extracted sub-charts' averages are between two various breakpoints. As a result, the approximate location (windows have overlap) and the length of the different size windows can be determined using generated sub-charts in slope chart. Finally, the denoised movement parameter profiles that were produced in step 1 will be divided in to sub-profiles using those windows. In Figure 3 for determining the size of sliding windows, we considered three breakpoints by splitting the area under the Gaussian curve into four equi-probable regions.

Figure 3: The process of determining the window sizes for dividing an MP profile

In Figure 3-b, $w_1, w_2, \dots$ denote the sliding windows, while Figure 3-c shows the resulting sliding windows on the movement parameter profile. The overlapping parts of subsequences are not shown.

If n is the number of breakpoints (the area under a Gaussian curve split in to $n+1$ equi-probable regions), the high value of n leads to small length windows while the small value of n gives large windows. As a result, selecting an optimal value for n is important and that influences the results directly. To determine the optimum n , we calculated the fitness value for $n=3,4,\dots,10$ using equation (5) where D is the maximum difference between the highest and average value in the extracted subsequences, and L is the maximum length of extracted subsequences.

$$F(n) = D/L \quad n = 3,4,\dots,10 \quad (5)$$

F tries to minimize the number of windows. Furthermore the differences in each subsequence should be minimized too. The smallest F indicates a valid optimal n .

Considering the fact that the appropriate window size to split each profile (by considering the slope homogeneity condition) can be different from the other profiles, the procedure used in this research is determining the appropriate windows size for each movement parameter profile and then aggregating the achieved different windows according to Figure 4.

Figure 4: Aggregation of windows

Feature extraction:

In the next step, the features should be extracted according to the generated subsequences in the previous stage. If m movement parameters are involved in the segmentation process, for all m subsequences generated using a window at specified time, the slope of the best fitting line will be calculated using least squares method. So, for each window we have a specified feature and the dimension of features is equal to the number of interfering movement parameters in the segmentation process. For example, by taking into account the two movement parameters (MP1 and MP2) in the segmentation process the feature extraction process has been shown according to Figure 5.

Figure 5: Feature extraction process

In Figure 5, the first feature extracted by the first window is equal to $(\frac{y_1}{x_1}, \frac{y_1'}{x_1'})$.

Automated feature clustering:

At the next step, the dataset including features extracted in previous procedure will be partitioned according to their distribution in space. For this purpose, we used Fuzzy c-means method as a well-known clustering algorithm. Finding the number of clusters (c) is a preliminary step in clustering data using FCM. There are many techniques proposed in the literature for this purpose. In this paper, we applied one of the most widely-used cluster validity indices proposed by Xie and Beni (XB) (Xie and Beni 1991). This index is computed using the formula (6).

$$V_{XB} = \frac{J}{Sep} = \frac{\sum \sum u_{ik}^m d^2(v_i, r_k)}{N \times \min_{i \neq j} d^2(v_i, v_j)} \quad (6)$$

where, $d(\cdot)$ stands for a distance function, c is the number of clusters, N is number of trajectories, v_i is i th cluster center, u_{ik} is membership degree of r_k to cluster center v_i and m ($m > 1$) is fuzzification coefficient. In (6), J evaluates the compactness of clusters and Sep estimates separation between cluster centers. A lower value of V_{XB} is desired.

To find an optimal number of clusters using XB, one may try various number of clusters $c=2$ to c_{max} , and select the one leading to the minimization of the objective function expressed in (6).

Representing each feature using the corresponding cluster center:

After clustering the extracted features, each feature will be shown using its cluster label, so in this step we can represent a trajectory using a sequence of limited number of cluster numbers which can be considered as a symbolic representation, and each cluster number (label) is representative of a specified behavior.

Proposed method evaluation:

Finally, the proposed method was compared to two different trajectory segmentation methods, namely the MP Class Sequences of Dodge et al. (2012) and the DWT-based segmentation of Soleymani et al. (2017), in two different applications. Experimental results are reported in the following section.

5. Experiments

We investigate the performance of the proposed methodology in two applications including trajectory clustering and movement pattern detection over some real data sets.

5.1. Trajectory clustering

In this section, we will evaluate the proposed trajectory segmentation approach for clustering trajectory datasets. The proposed method was implemented on North Atlantic hurricane trajectory dataset. This dataset, maintained by the National Hurricane Center, contains raw hurricane movement data recorded with a resolution of every 6 hours. According to the research in meteorology science, the dynamic behavior of hurricanes is influenced by two factors: the season of formation and the geographic latitude of the hurricanes. Elsner and Kara (1999) declared that the behavior of hurricanes which originate south of about 20° N (that they distinguished as low-latitude) is different from the hurricanes originating north of about 20° N (that they distinguished as high-latitude). Moreover, they showed that in North Atlantic Hurricanes, similarity in time of formation and origin location leads to similar dynamic characteristics. According to their findings, hurricanes that occur in similar seasons and have similar characteristics usually start from close locations (for example in the same quadrants with regard to $(19^{\circ}$ N, 80° W) (Dodge et al., 2012). We can use this information to evaluate our proposed approach. We extracted two clusters in the historical tracks of hurricanes and we assessed whether the results are consistent with the two classifications of the low-latitude and high-latitude hurricanes and origin east or west of 80° W. Moreover, we investigated the season of hurricanes in each cluster.

In this case study, our proposed method applied on 378 hurricane trajectories with a length longer than 40 points between the years 1851 and 2016. In Figure 6 the hurricane trajectories are shown.

Figure 6: Hurricane dataset

Since the hurricane dataset was obtained from NOAA, it did not contain a significant amount of noise, thus the DWT was not used in this experiment.

In the first step, by considering three movement parameters, speed, acceleration and turning angle, all trajectories in the dataset were segmented and converted into a symbolic representation using the proposed method. At the second step we divided the segmented trajectories into two clusters. Fuzzy k-medoids (Krishnapuram et al., 2001) was used to cluster the segmented data and Mann-Whitney U tests (Dodge et al., 2012) were used to see if the proposed method is able to differentiate between hurricanes of different months, or hurricanes with different origins p-values lower than 0.05 in each column indicate that there is a significant difference between the members of two clusters from the view of a specified attribute. In Table

3, the obtained p-values have been rounded to three decimal points; p-values lower than 0.05 are flagged with one star (*), p-values lower than 0.01 are flagged with two stars (**), and p-values lower than 0.001 are flagged with three stars (***).

Table 3: Results of Mann-Whitney U test on the resulting clusters

Method	Number of clusters	Low vs. high latitude origin	Origin east or west of 80° W	Season
Proposed Method	2	0.000 ***	0.000 ***	0.002 **
MP Class Sequences (Speed)	2	0.000 ***	0.002 **	0.034 *
MP Class Sequences (Turning angle)	2	0.000 ***	0.015 *	0.252
MP Class Sequences (Acceleration)	2	0.000 ***	0.008 **	0.083

The two clusters obtained by the proposed method show highly significant differences on all criteria related to the location of hurricanes' origin (low vs. high-latitude origin; origin west or east of 80° W) and regarding time-related attributes. The results achieved by the MP Class Sequences method (Dodge et al., 2012), where only the speed movement parameter is used in the segmentation process, show a highly significant difference in the hurricane origin criteria, but regarding the time of formation the difference at 0.034 is just barely significant. If the turning angle is used as the only participating parameter in the segmentation process using the MP Class Sequences method, the p-value in the Season column of Table 3 is no longer significant. The same holds for acceleration, though the difference in the longitude of origin is more significant than in the case of the turning angle. This suggests that both the turning angle and acceleration parameters are not good choices for generating results conforming to the above-mentioned meteorological facts.

In summary, the reported results indicate that in comparison to the MP Class Sequences segmentation method, when turning angle and acceleration are the selected parameters in the segmentation process, our proposed methodology is able to generate superior results in terms of distinguishing the significant difference between data with different time of formation.

To perform multiple comparisons between methods, a single factor ANOVA and Tukey's multiple comparison tests with a threshold of $p < 0.05$ are used in this study (Khalilpourazari et al., 2019; Khalilpourazari et al., 2018). For this purpose, the differences between two achieved clusters in each method in terms of considered attributes are computed over 10 independent runs. The P-values obtained from Tukey's method can be seen in Table 4. This table shows which pairs of methods are significantly different ($p\text{-value} < 0.05$).

Table 4: Results of Tukey's multiple comparison test on the resulting clusters

Methods	Low vs. high latitude origin	Origin east or west of 80° W	Season
Proposed Method- MP Class Sequences (Speed)	0.9762	0.000	0.000
Proposed Method- MP Class Sequences (Turning angle)	0.9762	0.000	0.000
Proposed Method- MP Class Sequences (Acceleration)	0.8458	0.000	0.000
MP Class Sequences (Speed)- MP Class Sequences (Turning angle)	1.0000	0.000	0.000
MP Class Sequences (Speed)- MP Class Sequences (Acceleration)	0.9762	0.025	0.003
MP Class Sequences (Turning angle)- MP Class Sequences (Acceleration)	0.9762	0.000	0.031

Tukey's post hoc comparisons revealed that with respect to origin east or west of 80 W and season our proposed method performs significantly better than three other methods in generating results consistent with the meteorological findings ($p\text{-value} < 0.05$). In addition, the P-values for the second columns are larger than 0.05, which means that there are no significant differences between all methods in terms of Low vs. high latitude origin.

5.2. Movement pattern detection (Turkey Vultures)

In this section three GPS tracks of turkey vultures (*C. aura*) from the interior North America population are considered for experimental studies. Turkey vultures migrate from Canada to South America and they pass over central regions of North America. There are four behavioral states (classes) during these birds' annual migrations over the year. The classes include: breeding season, non-breeding season, outbound migration, and return migration. Breeding season is when return migration ends and before beginning outbound migration. The period after stopping outbound migration and before starting return migration indicates the non-breeding or wintering season. Outbound migration refers to the time when migrants moved from their breeding grounds to their non-breeding grounds and finally the period when migrants moved from their non-breeding grounds to their breeding grounds which is called the return migration (Bildstein, 2006). These classes were identified by expert knowledge in Dodge et al. (2014) and provided valuable information for validating purposes.

In this study, by considering the two movement parameters speed and acceleration, the track of the individual Leo was used as training data. Note that by including other parameters such as turning angle, similar results were obtained, but for the sake of brevity we do not present these results. In order to illustrate the ability of the proposed method to discover behavioral modes, two annotated trajectories of individuals, Steamhouse 1 and Steamhouse 2 were applied as testing data. In Table 5 the property of each trajectory has been reported.

Table 5: Training and testing trajectories

Vulture Name	Tracking period	Number of fixes	The sampling rate	usage
Leo	16.06.2007 to 19.03.2013	11752	3h	Training data
Steamhouse 1	22.05.2009 to 18.03.2012	6500	3h	Testing data
Steamhouse 2	21.01.2010 to 19.03.2013	9500	3h	Testing data

The second column of Table 4 shows the date that the start and end points of each trajectory was recorded in. In the third column, the number of fixes (recorded coordinates) in each trajectory is shown and the forth column shows the temporal sampling rate in each trajectory.

Figure (7) shows track of Leo individual.

Figure 7: Leo's trajectories

After data preprocessing and cleaning we computed the movement parameter profiles for speed and acceleration for each trajectory using the fixes (lon, lat, t) of the movement trajectory data. These signals are the input signals for the wavelet transform. A Daubechies wavelet of degree 10 is selected as the mother wavelet, to extract the general pattern in the signal (Subasi 2007; Sur et al., 2014). There are other mother wavelet functions (e.g. Haar, Morlet, Mexican hat) however selecting the appropriate function depends on the application. For instance, certain wavelet functions are able to handle abrupt changes, while others may be best suited for linear changes in the movement (Daubechies 1990; Boggess and Narcowich 2009). For decomposing the movement signals through the DWT, a selection of appropriate decomposition levels is needed. According to the annotated data of Leo, the appropriate level of the approximation sub-bands for speed and acceleration is determined equal to 8. The proposed method implemented on the Leo trajectory and the clusters shorter than 100 fixes concatenated to adjacent clusters.

In Figure 8, we can compare the extracted clusters in the Leo individual trajectory to the data which is annotated using findings in Dodge et al, 2014.

Figure 8: Results of applying the proposed segmentation method on the Leo data. For the colors used in Figure 8-c, see the explanation in the text.

Figure 8-a shows the normalized profiles of speed and acceleration. According to Figure 8-b, we extracted the main patterns in the mentioned profiles using the discrete wavelet transform. As shown in Figure 8-c, four clusters were recognized by our proposed method in the Leo trajectory. The first cluster (Cluster 1) is including the segments where the speed is decreasing

and the acceleration is increasing (green parts in Figure 8-c). In other words, in this cluster the slope of speed is negative while the slope of acceleration is positive. In the second cluster (Cluster 2) the speed is increasing and the acceleration is decreasing (cyan parts in Figure 8-c) while the third cluster (Cluster 4) shows the segments in which both the speed and acceleration increase (blue parts). Finally, in the fourth cluster recognized by our method (Cluster 4), the slope of both speed and acceleration parameters is negative (red parts).

Focusing on a part of the annotated Leo trajectory (T), Figure 9 shows how the four extracted clusters can be merged to two different behaviors, migratory and non-migratory behaviors. Cluster 4 and Cluster 2 can be denoted as migratory pattern while Clusters 1, 2 and 3 with the arrangement shown in Figure 9-b form the non-migratory pattern.

Figure 9: Recognizing migratory vs. non-migratory states using the four detected clusters

By assigning the suitable clusters to the non-migratory pattern we can see that in the non-migratory pattern the speed will reach its lowest value, while in the migratory state the speed reaches its maximum. According to Dodge et al. (2014) a vulture's speed in non-migratory seasons on average is lower than the speed in migratory seasons. This confirms that the data annotation was well established. Furthermore the extracted clusters allow us to find more details on the vulture behaviors in two different patterns. For example, according to Figure 9, the maximum and minimum values for the acceleration parameter occur near behavioral change points.

As become evident from Figures 8-c and 8-d, 18 annotated segments have been extracted accurately for Leo out of a total of 19. The black part in figure 8-c is a non-migration season which was not retrieved correctly.

By considering the knowledge extracted from the training data, we implemented our proposed method on two other trajectories and tried to recover the behaviors identified by experts (Dodge et al., 2014). In Figure 10-a, the track of Steamhouse 1 is shown, which served as one of the test data sets in this study. Figures 10-b and 10-c show the states extracted from the Steamhouse 1 data and the annotated trajectory, respectively.

a: Steamhouse 1's trajectories

b: Resulting clusters

c: Annotated data

Figure 10: Applying the proposed segmentation method on the Steamhouse 1 data

By considering Breeding Ground and NonBreeding Ground as the non-migratory and spring and fall migration as the migratory behaviors, respectively, the proposed method was able to correctly distinguish the migratory from the non-migratory states.

In Figure 11 the tracking data, annotated trajectory and extracted states for a second testing data set, Steamhouse 2, are shown. There are 15 annotated segments in this data set and all of them seem to have been extracted correctly by our segmentation approach.

a: Steamhouse 2 trajectories

b: Resulting clusters

c: Annotated data

Figure 11: Applying the proposed segmentation method on the Steamhouse 2 data

To evaluate the performance of our proposed method, the outcomes of our segmentation method are compared with the DWT based segmentation method introduced by Soleymani et al. (2017).

To compare the performance of our method to the DWT based segmentation method, we count the number of extracted segments on the turkey vulture individuals for each method.

Table 6: Comparison of the retrieved and annotated behavioral segments

Track	Method	Number of annotated segments	Number of extracted segments
Leo (training)	DWT based method	19	18
	Proposed method		18
Steamhouse 1 (testing)	DWT based method	11	11
	Proposed method		11
Steamhouse 2 (testing)	DWT based method	15	15
	Proposed method		15

As shown in Table 6, both compared methods correctly identified all the annotated segments for Steamhouse 1 and Steamhouse 2 while both methods missed one segment in Leo trajectory. As a result, in terms of the number of retrieved behavioral segments, the results obtained by the two methods have the same quality.

The accuracy of detecting the change points between behavioral states (migratory vs. non-migratory) is another indicator to investigate the performance of our proposed method. Figure 12 shows the boxplots of the temporal difference in the change points between the extracted and annotation segments obtained by the two different methods.

Figure 12: Boxplots of temporal difference between retrieved and annotated segments in the turkey vulture trajectories

As shown in Figure 12 the proposed technique in this paper has produced lower (better) values for the considered performance indicator. Although for Steamhouse 2, the maximum temporal difference achieved by our method is higher than the maximum difference in the DWT based segmentation method, overall the average of the temporal differences in the extracted and annotated change points for Steamhouse 2 is lower in the proposed approach. In the results of method the average temporal difference in the change points between the extracted and the annotated segments is ~ 5 days (4.77) over the three individual trajectories. Given that the length of migratory segments is approximately in the range of 45 to 80 days (Soleymani et al., 2017), the achieved average accuracy for detecting change points seems rather good. In the DWT based segmentation method this value is ~ 6 days (6.06), as reported in Soleymani et al. (2017).

5.3. Movement pattern detection (white-fronted geese)

In order to investigate the migration strategies of white-fronted geese, Kölzsch et al. (2016) tracked a number of individuals using GPS transmitters during their spring and fall migration period over one year. In this dataset the trajectories are collected as the GPS positions and each position is labeled as either spring migration or fall migration which describes the behavioral mode of the bird (Kölzsch et al., 2016).

For validation purposes, we used the trajectories of 6 individuals that started their spring migration from the Netherlands to the breeding grounds in the west of Russia. Since the quality of tags used in 2013–2014 was better and the GPS tracks had most data points in these years, all trajectories in this experiment were selected from the trajectories collected in 2013–2014.

By considering two parameters, speed and acceleration, we used the track of Individual 712 as the training data. Similar to the previous section, including other parameters in the segmentation process will not change the results but removing speed or acceleration parameters will corrupt the quality of results. For retrieving behavioral states Individuals 742, 3104, 3276, 3097 and 3267 were considered as the testing data.

Since in the white-fronted geese migration dataset, positions are provided in different time resolutions, all data were resampled to 6h in order to use the same decomposition level for all the individuals. Table 7 shows the properties of each trajectory.

Table 7: The property of training and testing trajectories

Individual id	Tracking period	Number of fixes	usage
712	09.03.2014 to 04.10.2014	3172	Testing data
742	20.03.2014 to 03.10.2014	995	Training data
3084	30.08.2013 to 06.07.2014	6421	Testing data
3104	14.03.2014 to 01.10.2014	6058	Testing data
3097	29.08.2013 to 05.06.2014	8398	Testing data
3267	19.03.2014 to 06.06.2014	529	Testing data

The second column of Table 7 is assigned to the start and end date of recording each trajectory and the number of recorded points in each trajectory is reported in the third column. The fourth column shows the dataset usage in the validation process. In Figure 13 trajectories of the considered individuals are shown.

Figure 13: White fronted geese dataset

For each individual the movement parameter profiles, speed and acceleration, are derived from the coordinates recorded in each trajectory. According to the annotated Individual 712, a Daubechies wavelet of degree 10 is used as the mother wavelet and the level of the approximation sub-bands is set equal to 8 for the speed and acceleration profiles. In addition,

the short clusters achieved by the proposed segmentation method are concatenated to adjacent clusters.

Figure 14 shows how the extracted clusters in the training and testing individuals' trajectories can be matched to the data that is annotated based on the behavioral states of individuals during the spring and fall migration periods, respectively.

Figure 14: Applying the proposed segmentation method on white fronted geese data

In Figure 14-a, two different behaviors including spring migration and fall migration in the training data are shown. According to this figure in the white fronted geese dataset no data has been collected in the breeding grounds. Figure 14-b shows the extracted three clusters in trajectory of the training individual based on the normalized profiles of speed and acceleration. In the first cluster (Cluster 1) the speed is decreasing and the acceleration is increasing. The second cluster (Cluster 2) includes the segments where the speed is increasing and the acceleration is decreasing, while the third cluster (Cluster 3) shows the segments in which both the speed and acceleration increase. In this figure we show how the three detected clusters in this study can be used in retrieving two different behaviors, spring migration (a) and fall migration (b), from the trajectory of the training data.

We tested our method on five different trajectories. In Figures 14-c and 14-d the two behavioral modes spring migration and fall migration are recognized correctly (Individuals 742 and 3084). Figures 14-e and 14-f show that our method could detect the spring migration in Individual 3104 and the migration in Individual 3097 correctly, while the performance of these two individuals was different in the fall migration and spring migration, respectively. Furthermore, Figure 14-g shows the track of Individual 3276, which was tracked during the spring migration. Our method performed successfully in detecting the correct behavior in this individual.

To measure the efficiency of our proposed method in comparison to others, we compared the achieved results with a hierarchical clustering-based segmentation method proposed by Teimouri et al. (2018), which was reviewed in Section 2. According to the studies by Kölzsch et al. (2016) and Deng et al. (2019) in the white fronted geese dataset (*Anser A. albifrons*) migration speed is significantly different between the two seasons, while there is an insignificant (negligible) difference in straightness indices of both migration seasons. We used this information to modify the hierarchical clustering-based segmentation method in extracting two different behavioral modes, fall migration and spring migration. In Table 8 we compared the overall precision achieved by two different methods.

Table 8: The precision achieved by two methods in detecting behavioral modes (white fronted geese data)

Methods	Fall	Spring
Hierarchical clustering based segmentation	52.32%	57.86%
Our method	80.00%	83.30%

For obtaining the precision we computed the summation of times that the algorithm detected a behavior correctly, divided by the summation of times that an individual has that specified behavior. The overall precision can be calculated by averaging the precision in all considered individuals. According to Table 8 our method obviously outperformed the hierarchical clustering-based segmentation method by Teimouri et al. (2018) in detecting both different states.

6. Discussion

Using the symbolic representation to represent trajectories leads to reduced storage costs of trajectory data. In most symbolic dimension reduction techniques based on movement parameters such as the MP Class Sequences method (Dodge et al., 2012) or movement pattern strings method (Chen et al., 2004), the usual procedure is to partition the range of movement parameters into several parts and representing each value falling into a particular range with the symbol assigned to the corresponding class. By involving more movement parameters in the segmentation process the number of classes and so the number of symbols can potentially be

increased significantly. One of the most important advantages of the proposed method in this paper is its simultaneous use of several movement parameters in the segmentation process, representing a long trajectory with only a limited number of labels. Representing the strings using a small number of characters reduces the costs of the pattern matching and retrieval, an issue that becomes more important in large datasets (Du Mouza et al., 2006).

On the other hand, the process of delimiting the range of a movement parameter value with the goal of assigning each range to a distinct symbol needs some user-defined thresholds. An important feature of the proposed technique is that it does not require input parameters, as the ranges of movement parameters values are obtained automatically using a clustering process.

As shown in Section (5-1) the results obtained by the MP Class Sequences method, in which the speed movement parameters are considered in the segmentation process, show significant difference in hurricane origin attributes and the time of formation, while the results achieved from turning angle are not as convincing as for speed. As a result applying an appropriate movement parameter in the segmentation process is an important task in the MP Class Sequences method. In our proposed method, more than one parameter can participate in the segmentation process and the segments of a trajectory which are in the same clusters are similar in different aspects. For example, if we take into account three movement parameters including turning angle, speed and acceleration in segmentation process, the segments in each cluster are homogenous in terms of turning angle, speed and acceleration. Therefore the problem of selecting suitable parameters in the segmentation process in MP Class Sequences method has been solved in our proposed technique.

The movement parameter profiles such as speed, acceleration, turning angle, displacement, straightness index and so on can be computed using the position data. Existence of noise in the position of trajectory points may lead to errors in the movement parameters calculation. As a result the segmentation techniques with a local view of datasets (such as the MP Class Sequences method) are not appropriate for noisy data. Using sliding windows in our proposed technique (when dealing with noisy data) reinforces the global trend of a trajectory in each window and so potential errors caused by noise will be reduced. On the other hand in this study the wavelet transform is used in order to remove noise from the long movement parameter profiles.

Experimental studies in Section (5-2) indicate the effectiveness of the proposed method in extracting movement behavior from long noisy movement trajectories (Turkey vultures).

However, using the wavelet transform also has its disadvantages. The most important one is the edge effects at the beginning and at the end of the signals, which is known as “cone of influence”. Padding time series with sufficient zeros (Torrence and Compo 1998) or removing the segments affected by the cone of influence are the common ways to decrease edge effects, but it is impossible to eliminate edge effects completely.

In our method, we use the approximation sub-bands of the DWT for noise removal, requiring only a single input parameter, that is, the approximation sub-band level. The segmentation method by Soleymani et al. (2017) makes use of both the approximation and detail sub-bands of the DWT, and hence requires more input parameters, including the approximation sub-band level, detail sub-band level, peak threshold, and detail sub-band coefficients threshold, which are selected by visual inspection of annotated data or prior knowledge about the target behavior. Invariably, this renders the parameterization of their method more complex and demanding. Furthermore, their technique works on only one movement parameter during the segmentation process, creating the challenge of selecting a suitable movement parameter.

Finally in Section (5-3) our proposed method significantly performed better than a hierarchical clustering-based segmentation method proposed by Teimouri et al. (2018) in identifying two different behavioral modes in white fronted geese data. The results indicate that when there is no significant difference between the persistence velocity values or the turning velocity values in different behaviors of an animal (such as spring migration and fall migration), the hierarchical clustering-based segmentation method does not perform as well as the cases where the differences in persistence velocity or turning velocity values are significant (such as resting and walking). On the other hand, as mentioned earlier, in some cases there is valuable information in a specified movement parameter profile and the method which uses multiple movement parameters in segmentation process simultaneously can produce more effective results.

7. Conclusion

In this paper a trajectory segmentation method using the concept of clustering has been introduced. The proposed method is based on the segmentation of movement parameter profiles of an object over time. Using this technique we can represent a long noisy trajectory with only a limited number of labels.

In order to evaluate the proposed segmentation approach we investigated the performance of the methodology in two applications including trajectory clustering and movement behavior extraction, applied to real data sets. Furthermore, we evaluated our approach in comparison to three relevant methods (Dodge et al., 2012; Soleymani et al., 2017; Teimouri et al., 2018). The experiments showed that the proposed method is able to generate appropriate results in finding the existing patterns in the movement datasets, and it exhibits equal or better performance than the respective baseline methods. Particularly, when the data contains a significant amount of noise, the presented method works effectively. We demonstrated that considering different movement parameters in the segmentation process simultaneously increases the reliability of the results. The main reasons for the superior performance of the proposed method are first, its simultaneous use of multiple movement parameters in the segmentation process, which leads to extracting change points in moving object behavior with a more comprehensive view; and second, defining appropriate variably sized windows supports the algorithm in recognizing the behavioral change points with an improved accuracy.

For future work, adapting the proposed technique for different characteristics of different movement parameters in separately adjusted windows e.g. for the slope of speed, the average of speed in a window, etc., may be a possible extension of the proposed methodology. Moreover, we plan to extend our proposed approach by integrating contextual data. Finally, the performance of the method in this paper can be investigated over other distance functions.

References

- Ahearn, S.C. and Dodge, S., 2018. Recursive multi-frequency segmentation of movement trajectories (ReMuS). *Methods in Ecology and Evolution*, 9 (4), 1075–1087.
- Bezdek J.C., 1981. *Pattern Recognition with Fuzzy Objective Function Algorithms*. Plenum Press.
- Bildstein KL, 2006. *Migrating raptors of the world: their ecology and conservation*. Ithaca, NY: Cornell University Press.
- Boggess A , Narcowich F.J, 2009. *A First Course in Wavelets with Fourier Analysis*, John Wiley and Sons, Hoboken, NJ, USA.

- Chakravarty P, Cozzi G, Ozgul A, Aminian K, 2019. A novel biomechanical approach for animal behaviour recognition using accelerometers, *Methods in Ecology and Evolution*.
- Chen L, Ozsu M.T, and Oria V, 2004. Symbolic Representation and Retrieval of Moving Object Trajectories. In: MIR '04: Proceedings of the 6th ACM SIGMM international workshop on Multimedia information retrieval In Proc. of the ACM SIGMM international workshop on multimedia information retrieval, 227–234.
- Chen Z, Liu J, Y Deng, He K, Hopcroft J, 2019. Adaptive Wavelet Clustering for Highly Noisy Data. 35th International Conference on Data Engineering (ICDE), 8-11 April, Macao.
- Damiani M, Hachem F, Issa H, Ranc N, Moorcroft P, Cagnacci F, 2018. Cluster-based trajectory segmentation with local noise. *Data Min. Knowl. Discov.*, 32(4):1017– 1055.
- Daubechies I, 1990. The wavelet transform, time-frequency localization and signal analysis. *IEEE Transactions on Information Theory*, 36, 961–1005.
- Deng X, Zhao Q, Fang L. et al, 2019. Spring migration duration exceeds that of autumn migration in Far East Asian Greater White-fronted Geese (*Anser albifrons*), *Avian Res* 10.
- Dodge S, Bohrer G, Bildstein K. et al, 2014. Environmental drivers of variability in the movement ecology of turkey vultures (*Cathartes aura*) in North and South America. *Philosophical Transactions of the Royal Society of London B: Biological Sciences*, 369, 20130195.
- Dodge S, Laube P, Weibel R, 2012. Movement similarity assessment using symbolic representation of trajectories. *Int J Geogr Inf Sci* 26, 1563–1588
- Dodge S, Weibel R and Laube P, 2011. Trajectory Similarity Analysis in Movement Parameter Space. *Proc of GISRUK*.
- Dodge S, Weibel R, Forootan E, 2009. Revealing the physics of movement: comparing the similarity of movement characteristics of different types of moving objects. *Computers, Environment and Urban Systems*, 33: 419–434.
- Du Mouza C, Rigaux P, Scholl, M, 2006. On-line Aggregation and Filtering of Pattern-based Queries. In: *Scientific and Statistical Database Management*, 18th International Conference on IEEE, 333–342.
- Eckley D. C, Curtin K. M, 2013. Evaluating the spatiotemporal clustering of traffic incidents. *Computers, Environment and Urban Systems*, 37, 70-81
- Egiazarian K, Katkovnik V, Öktem H and Astola J, 2000. Transform-based denoising with window size adaptive to unknown smoothness of the signal, In *Proc. of First International Workshop on Spectral Techniques and Logic Design for Future Digital Systems (SPECLOG)*, Tampere, Finland, 409-430.
- Elsner J, Kara A, 1999. *Hurricanes of the North Atlantic: Climate and society*. New York Oxford: Oxford University Press.
- Faloutsos C, Ranganathan M, Manolopoulos Y, 1994. Fast subsequence matching in timeseries databases, *Procs of the ACM SIGMOD Conference on Management of Data*, Minneapolis, Minnesota, May 24-27, 419 -429.
- Gurarie E, Andrews R.D, Laidre K.L, 2009. A novel method for identifying behavioural changes in animal movement data. *Ecol. Lett*, 12, 395–408.
- Gurarie E, Bracis C, Delgado M, Meckley T. D, Kojola I, & Wagner, C. M, 2016. What is the animal doing? Tools for exploring behavioral structure in animal movements. *Journal of Animal Ecology*, 85(1), 69–84.
- Izakian H, Pedrycz W, Jamal I, 2015. Fuzzy clustering of time series data using dynamic time warping distance. *Eng Appl Artif Intell*, 235–244.
- Izakian Z, Mesgari M.S, Abraham A, 2016. Automated clustering of trajectory data using a particle swarm optimization. *Comput. Environ. Urban. Syst*, 55, 55–65.
- Jain A.K, 1989. *Fundamentals of Digital Image Processing*, Englewood Cliffs, NJ: PrenticeHall.
- Khalilpourazari S, Pasandideh SHR, Ghodrtnama A (2018) Robust possibilistic programming for multi-item EOQ model with defective supply batches: Whale Optimization and Water Cycle Algorithms. *Neural Computing and Applications*, (in-press).

- Khalilpourazari S, Pasandideh SHR, Niaki STA, 2019. Optimizing a multi-item economic order quantity problem with imperfect items, inspection errors, and backorders. *Soft Comput* 23:1–28.
- Kölzsch A, Müskens GJDM, Kruckenberg H, Glazov P, Weinzierl R, Nolet BA, Wikelski M, 2016. Towards a new understanding of migration timing: slower spring than autumn migration in geese reflects different decision rules for stopover use and departure. *Oikos*, 125:1496–507.
- Korn F, Jagadish H.V, Faloutsos C, 1997. Efficiently Supporting Ad Hoc Queries in Large Datasets of Time Sequences, *Proc of ACM SIGMOD Conf. Management of Data*, Tucson, Arizona, USA, May 13-15, 289–300.
- Krishnapuram R, Joshi A, Nasraoui O, Yi L, 2001. Low-complexity fuzzy relational clustering algorithms for web mining, *IEEE Trans. Fuzzy Syst*, 9(4), 595 -608.
- Laube P, Dennis T, Forer P, Walker M, 2007. Movement beyond the snapshot - Dynamic analysis of geospatial lifelines *Computers, Journal of Environment and Urban Systems*, 31: 481-501.
- Laube P, Imfeld S and Weibel R, 2005. Discovering relative motion patterns in groups of moving point objects. *International Journal of Geographic Information Science*, Taylor & Francis Group. 639–668.
- Lin J, Keogh E, Lonardi S, Chiu B, 2003. A symbolic representation of time series, with implications for streaming algorithms, *Workshop on Research Issues in Data Mining and Knowledge Discovery*, the 8th ACM SIGMOD, San Diego, CA.
- Sharif M, Alesheikh AA, 2017. Context-awareness in similarity measures and pattern discoveries of trajectories: a context-based dynamic time warping method. *GISci Remote Sens*, 54:426–452.
- Soleymani A, Pennekamp F, Dodge S, Weibel R, 2017. Characterizing change points and continuous transitions in movement behaviours using wavelet decomposition. *Methods in Ecology and Evolution*, 8, 1113–1123.
- Subasi A, 2007. EEG signal classification using wavelet feature extraction and a mixture of expert model. *Expert Systems with Applications*, 32, 1084–1093.
- Sur M, Skidmore A.K, Exo K.-M, Wang T, Ens B.J, Toxopeus a.G, 2014. Change detection in animal movement using discrete wavelet analysis. *Ecological Informatics*, 20, 47–57
- Teimouri M, Indahl U, Sickel H, Tveite H, 2018. Deriving animal movement behaviors using movement parameters extracted from location data. *ISPRS Int. J. Geo-Inf.*
- Torrence C, Compo GP, 1998. A practical guide to wavelet analysis, *Bull Am Meteorol Soc* 79, 61–78.
- van Toor ML, Newman SH, Takekawa JY, Wegmann M, Safi K, 2016. Temporal segmentation of animal trajectories informed by habitat use. *Ecosphere* 7:e01498.
- Xie X.L, Beni G, 1991. A validity measure for fuzzy clustering, *IEEE Trans. Pattern Analysis and Machine Intelligence*, 13(8), 841 -847.
- Zhang J, O'Reilly K.M, Perry G.L.W, Taylor G.A, Dennis T.E, 2015. Extending the Functionality of Behavioural Change-Point Analysis with k-Means Clustering: A Case Study with the Little Penguin (*Eudyptula minor*). *PLoS ONE* 2015, 10, e0122811.
- Zheng Y, Li Q, Chen Y, Xie X, Ma W, 2008. Understanding mobility based on GPS data, *Proceedings of the 10th international conference on Ubiquitous computing*, September 21-24, Seoul, Korea.