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Revealing the Physics of Movement: Comparing the Similarity of Movement Characteristics of Different Types of Moving Objects

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Abstract

We propose a segmentation and feature extraction method for trajectories of moving objects. The methodology consists of three stages: trajectory data preparation; global descriptors computation; and local feature extraction. The key element is an algorithm that decomposes the profiles generated for different movement parameters (velocity, acceleration etc.) using variations in sinuosity and deviation from the median line. Hence, the methodology enables the extraction of local movement features in addition to global ones that are essential for modeling and analyzing moving objects in applications such as trajectory classification, simulation and extraction of movement patterns. As a case study, we show how the method can be employed in classifying trajectory data generated by unknown moving objects and assigning them to known types of moving objects, whose movement characteristics have been previously learned. We have conducted a series of experiments that provide evidence about the similarities and differences that exist among different types of moving objects. The experiments show that the methodology can be successfully applied in automatic transport mode detection. It is also shown that eye movement data cannot be successfully used as a proxy of full-body movement of humans, or vehicles.

Keywords: Moving point data mining; moving object; movement parameters; movement behavior; trajectory decomposition; trajectory classification

1 Introduction

The analysis of trajectories of moving objects has recently become the focus of many research projects in the area of geographic information science (GIS), human-computer interaction (HCI), ecology, biology, social and behavioral sciences. Simulating human and animal mobility behavior, or studying human interaction with computers are emerging into an interesting area of research, which requires extracting knowledge about the dynamic behavior of different types of agents and thus challenges developing new exploratory data analysis methods on massive movement datasets. Therefore, many spatio-temporal data mining algorithms and analytical methods have been proposed at the theoretical level, however few of them have been implemented and applied in practice to date.

A critical success factor for empirically based research is the availability of relevant data. The main problem is that data about moving point objects (MPOs) are not easily available and accessible due to data cost, security and privacy issues (Giannotti & Pedreschi, 2007). In order to overcome the problem of data scarcity, one may consider utilizing data that can act as a proxy of 'physical' movement data or benefit from artificial, simulated movement data (Blythe et al., 1996). For instance, bank note dispersals can be considered as a proxy for human movement given that money is carried by individuals (González et al., 2008), or mouse movement traces as a proxy of eye movement data in HCI studies (Chen et al., 2001; Cox et al., 2006). Similarly, eye movement data from human subject experiments on graphic displays is potentially of interest to be used as a proxy of other types of moving objects, as it is relatively inexpensive to collect and usually not subject to particular privacy issues.

By the same token, the simulation of trajectories is used for diverse purposes, such as ecological modeling (Turchin, 1998), spatio-temporal database research (Pfoser & Theodoridis, 2003), agent-based pedestrian modeling (Batty, 2003), and in the evaluation of data mining algorithms (Laube & Purves, 2006). Therefore, detailed knowledge of the movement parameters of different MPOs is crucial in choosing the best representative proxy in trajectory simulation. The better the knowledge about the movement behavior of the particular objects that is simulated, the more realistic the simulation results will be. However, there are still some open research questions in the field of modeling and simulating trajectories of moving objects. For instance, how can we efficiently assess the similarity of the behavior of the simulated or proxy data in comparison to the original moving object? Is it possible to automatically identify trajectories of unknown objects by applying our knowledge about the movement

behavior of similar known objects whose movement characteristics have been previously learned by the system?

The above issues all point to a need for methods for analyzing the movement behavior of different MPOs, with the aim of determining the similarity of trajectories generated by different MPOs. Similarity search, that is, trying to find similar trajectories of moving objects, is a fairly new topic in spatial data mining. Most of the techniques proposed to date are looking for similarities of the geometric shape of the trajectories based on a distance function. Examples include the Edit Distance on Real sequence (EDR) (Chen et al., 2005), One-Way Distance (OWD) (Lin & Su, 2008), Euclidean and Time Wrapping distance and Longest Common Subsequence (LCSS) (Vlachos et al. 2002). However, we are more interested in finding similarities in movement behavior of *different types* of moving objects. Therefore, our motivation is to take an analytical look at the movement characteristics and dynamic behavior of different types of dynamic objects such as humans, vehicles and eye movements and extract possible similarities among movement behavior of such objects. Consequently, we want to see whether we can predict the types of unknown MPOs by similarity to the trajectories of previously learned MPOs.

This article thus presents a methodology that allows extracting movement parameters from the trajectories of different types of moving objects. The key element of the methodology is an algorithm that decomposes the profiles generated for different movement parameters using variations in sinuosity and deviation from the median line, hence enabling the extraction of local movement features in addition to global ones.

Our proposed methodology is useful in several respects. It can inform developers of pattern recognition and data mining algorithms about similar and dissimilar types of moving objects, hence allowing to design rigorous algorithm evaluation strategies. It can help answer the question how similar simulated or proxy MPOs are to the corresponding reference MPOs. The proposed trajectory segmentation algorithm yields subtrajectories that can facilitate similarity search. The methodology generates relevant movement attributes at the global level of the entire trajectory as well as at the local level of segments of homogeneous movement characteristics, enabling more differentiated parameterization of trajectory simulations. Thus, it can be used to answer to the above-mentioned research questions in simulation studies. And finally, it can be used to classify unknown moving objects into previously learned MPO types, in data mining operations on large trajectory databases or in real-time applications. For instance, it can be used in transportation research to detect the transport mode in anonymized trajectories of different transportation objects (e.g. cars, motorcycles, bicycles, pedestrian).

The remainder of the paper is organized as follows. We start in Section 2 with a brief introduction of moving point objects and a review of the relevant literature. We continue in Section 3 by explaining the proposed methodology for feature extraction of movement parameters. In section 4, we propound some possible applications of the proposed methodology. In Section 5, we report the experiments conducted to validate the three steps of the methodology following the classification process. Section 6 provides a detailed discussion of the experimental results. We end in Section 7 with conclusions and an outlook.

2 Moving Point Objects (MPO)

We define moving objects as entities whose positions or geometric attributes change over time. In many applications moving objects are considered as moving points, ignoring the dimension of the object. In (Dodge et al., 2008), moving objects are categorized into two major groups of geo-referenced (i.e. dynamic objects that move about in geographic space) and non-geo-referenced (i.e. dynamic phenomena that move in a non-geographic space) dynamic objects. Accordingly, geographically referenced object such as humans, animals or vehicles belong to the first group, while gaze point movements in eye movement studies can be mentioned as an example for the other group. Each of these dynamic objects, to a varying degree, shares some similarities but also exhibits differences to the others in terms of the corresponding data structure, dynamic behavior and nature of movement.

In general, the path of a moving object, named trajectory, is the subject of interest in moving object data analysis. A trajectory is defined as a sequence of successive positions of the moving object over a period of time and thus can be considered as a time series of spatial data in data mining tasks (Spaccapietra et al., 2008). In order to analyze or simulate the behavior of a moving object we need to have detailed information about the trajectory of the object as well as information about the environmental conditions related to the trajectory (Spaccapietra et al., 2008). In other words, it is necessary to extract differentiated movement parameters of a trajectory in order to analyze or simulate typical movement behavior of an object. In this regard many attempts have recently been carried out in the field of modeling and analyzing trajectories and moving object data mining. Giannotti & Pedreschi (2007) give an overview of the history of analyzing moving objects from the initial idea of time geography to the recent advances in knowledge discovery from moving objects using spatiotemporal data mining techniques, including latest attempts on data privacy and security issues. Batty (2003) applied   4agent-based modeling of individual and

collective behavior of pedestrians to show how randomness and geometry are important to local movement and how individuals respond to locational patterns. Brillinger et al. (2004) developed a stochastic differential equation-based model for exploratory data analysis of the trajectories of deer and elk to describe movement behavior of free-ranging animals. They tried to extract typical parameters of data obtained from animal telemetry studies. Laube and Purves (2006) considered modeling relative movement within groups of objects in order to evaluate extracted movement patterns by simulation through correlated random walk procedures. Hornsby and Cole (2007) focused on modeling moving objects from an event-based perspective and tried to detect movement patterns by analysis of different events. Other researchers have focused on differentiating and modeling moving objects in movement imagery databases, in order to describe and classify behavior of moving objects in computer vision systems using sequences of images (Zheng et al., 2005; Agouris et al., 2003; Ozyildiz et al., 2002). In Naftel & Khalid (2006) another approach for clustering and classification of object trajectory-based video clips using spatiotemporal function approximation has been proposed. Bashir et al. (2007) present a classification algorithm for recognizing object activity using trajectory of objects. In the proposed classification method, trajectories are segmented at points of change in curvature and the sub-trajectories are represented by their principal component analysis (PCA) coefficients (Bashir et al., 2007). In Bay & Pazzani (2001) a search algorithm for mining contrast sets has been developed to differentiate between several contrasting groups (e.g. male or female students, or the same group over time) from observational multivariate data.

The above-mentioned modeling and classification techniques have mainly been applied on trajectories obtained from the same MPO types. Fewer studies exist on the classification and differentiation of trajectories of different kinds of moving objects. One domain where the comparison of trajectories from different moving objects is relevant is the field of transportation studies, specifically in the analysis of transport behavior in urban environment. In this domain some researchers focused on extracting knowledge from raw GPS data to detect the mode of transport that people used, with the aim of understanding user behavior (Zheng et al., 2008). For instance, Zheng et al. (2008) proposed an approach based on supervised learning to automatically learn the transportation mode, including walking, taking a bus, riding a bike and driving. Their method is comprised of a segmentation method based on change points (i.e. where the mode of transport presumably changes), an inference model (i.e. decision tree, support vector machine (SVM), Bayesian net, or conditional random field (CRF)), and a post processing method. In this study the four above-mentioned inference models have been evaluated. They show that the higher accuracy is obtained from the decision

tree model. In another study, Tsui and Shalaby (2006) introduced a fuzzy logic approach. They applied a segmentation method based on three types of mode transfer points (MTP). In a similar study, Schlüssler and Axhausen (2009) applied the same method based on speed and acceleration characteristics to distinguish five modes of transport (i.e. walk, cycle, car, urban public transport, and rail). Moreover, Zheng et al. (2008), Schlüssler and Axhausen (2009) give a summary of other related research. To the best of our knowledge, almost all the proposed methods have difficulty distinguishing different transport modes in congestion or heavy traffic. They also do not seem effective in distinguishing the transport mode of vehicles with similar speed range. Finally, they appear having difficulties to detect the correct transport mode when people only take one kind of transport mode during a trip. Therefore, there is still a need for more research on more reliable approaches for transport mode detection.

In Dodge et al. (2008), Giannotti & Pedreschi (2007) and Laube et al. (2007) parameters of a trajectory generated by a moving object are introduced such as speed, acceleration, duration of movement, sinuosity, traveled path, displacement, and direction. These descriptors form fundamental building blocks for characterizing the movement of an object and can be defined in an absolute sense (i.e. with respect to the external reference system) or in a relative sense, (i.e. in relation to the movement of other MPOs or to the previous states of the same MPO). Generally speaking, different types of moving objects, depending on the particular physics of their movement, to some degree exhibit different signatures of such movement descriptors. Each MPO has a typical dynamic behavior, which to some extent is similar for individuals of the same kind. Consequently, moving objects can be reproduced (simulated) according to the typical behavior of the similar sort of objects, or objects having the same dynamic behavior (Laube & Purves, 2006). Likewise, the typical behavior of different objects can be extracted from the particular parameters of their trajectories using the above-mentioned descriptors.

Therefore, we propose a methodology that allows extracting such movement parameters from the trajectories of different types of moving objects and classifying trajectories of unknown MPOs by similarity to the known trajectories. We focus on the characterization and classification of *different types* of moving objects and we conduct a comparative analysis and classification of the movement behavior of different objects, manifested through their trajectories. As a case study, we show how our model can be applied in the classification and prediction of transport mode of unknown trajectories of people using a supervised classification method. The following section describes our methodology in detail.

3 Methodology

Our methodology consists of three steps, shown graphically in Figure 1 and expanded on in the remainder of this section: 1) trajectory data preparation; 2) global descriptors computation; and 3) local feature extraction. The products generated from applying this procedure can directly be used for other purposes, such as generating inputs for movement simulators, or trajectory classification as presented later in Section 4.
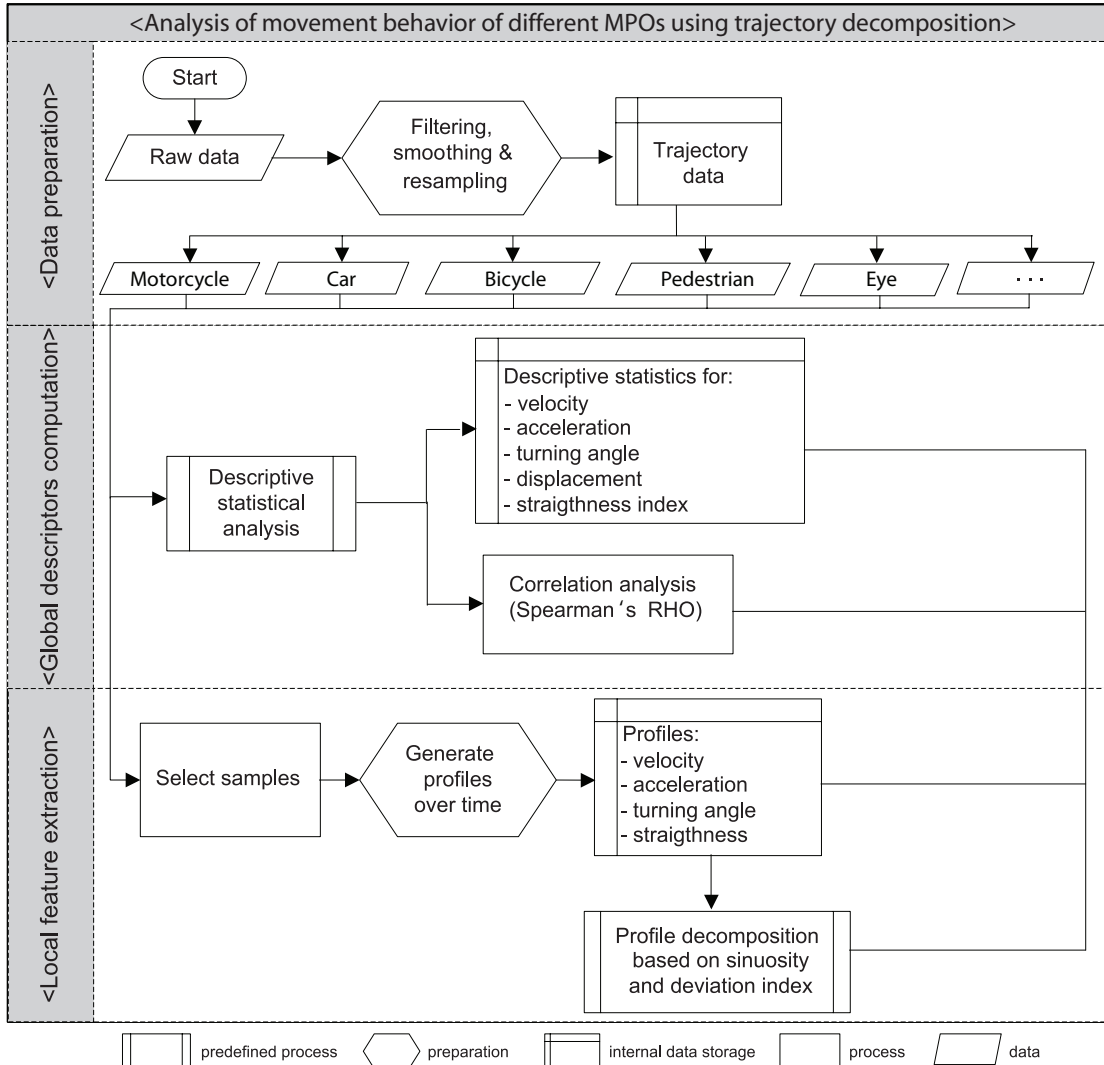
Fig. 1. Methodology for analyzing and extracting the movement behavior of different MPOs

3.1 Trajectory data preparation

Raw data captured by movement tracking devices usually to some degree contain noise, outliers and gaps, depending on the nominal precision and accuracy of the tracker as well as other factors that influence the completeness, accuracy and reliability of fixes. The accuracy of GPS observations, especially in absolute positioning, is very

7

sensitive to the existence of obstacles that block GPS signals, multi-path effects, ionospheric and tropospheric errors etc. (Hoffmann et al, 2001). In kinematic GPS surveys used to generate trajectory data of the type used in this study, it seems reasonable to assume an accuracy of 5-10 meters for practical purposes. Eye trackers have a higher accuracy (i.e. 0.5 degree) and sample eye movements at fine temporal granularity (e.g. about 20 milliseconds). However, raw data generated by eye trackers still contain a considerable amount of noise, outliers, and gaps, which should be remedied in order to achieve better results. Therefore, in order to remove effects of noise and positioning errors of the tracking devices and other factors, we recommend applying data cleaning and pre-processing procedures on the raw data to achieve more reliable trajectories. The pre-processing phase consists of three steps including filtering, re-sampling, and smoothing. During the filtering process outliers are removed from the raw data, namely those fixes that had a distance from the previous fix of more than three times the standard deviation (3σ) of the distances between consecutive fixes. The re-sampling procedure then generates a trajectory at regular intervals by linear interpolation along the trajectory. Finally, the smoothing step eliminates noise remaining in the data. In order to smooth raw GPS data several methods can be employed, such as least squares, spline approximation, moving average, Kernel-based smoothing, and Kalman filtering (Eubank, 2005). In this regard, Jun et al. (2007) developed an analytical study of different smoothing methods and proposed a modified version of Kalman filtering to be applied for GPS data containing errors. (See Section 5.2.1)

3.2 Computation of global descriptors

Movement parameters (i.e. speed, acceleration, turning angle, straightness, etc.) can be derived from the trajectory of an object and thus describe the dynamic behavior of the object. These descriptors are very different in terms of the values that they can take for each type of MPO. For instance, eyes can move quickly in fractions of a second from one end of a picture to the other in an almost mass-less movement, while the acceleration of human whole-body motion is governed by greater mass and inertia.

In order to evaluate the movement behavior inherent to the given trajectory data sets, various movement parameters can be computed for each point (fix) along a trajectory: for instance speed (i.e. rate of change of the object's position); acceleration (i.e. rate of change of the object's speed); turning angle (i.e. direction of the movement); displacement (i.e. the beeline connector distance between two consecutive points); traveled path (i.e. the path length along the trajectory); and straightness index (i.e.

8

the ratio of the traveled path and displacement); giving an indication of the sinuosity of the trajectory at a specific point (Dodge et al., 2008; Benhamou, 2004; Laube et al., 2007).

To achieve differentiated results in the characterization of trajectories, we propose that the computation of movement parameters proceeds at consecutive levels of refinement. That is, the process should first take a global look, computing descriptive statistics for the entire trajectory. Then, it should zoom in to extract local information of the trajectories at finer resolutions. Finally, in order to reveal more detail in the movement behavior of the selected objects and make their trajectories comparable, we propose to decompose the computed profiles of movement parameters to a set of meaningful subsections (or segments). Sections 3.2.1 and 3.2.2 describe the computation of global descriptors; Section 3.3 describes the extraction of local movement descriptors and the profile decomposition.

3.2.1 *Global descriptive statistics*

In order to extract the global movement properties of a given MPO, the above-mentioned movement parameters are first derived from the entire trajectory of the object. Next, global descriptive statistics of the movement parameters are computed such as the minimum, maximum, mean, median, standard deviation, variance and skewness over the entire trajectory.

3.2.2 *Correlation analysis*

In order to assess potential interrelationships between movement parameters, a correlation analysis should be carried out after extracting the movement parameters of given MPOs. We recommend computing Spearman Rank Correlation (RHO) as a non-parametric measure of correlation, since it has the advantage of making no assumptions about the frequency distribution of the variables (Chatfield, 1989). It is used to test the direction and strength of the relationship between variables. High correlations between movement parameters suggest that some variables may be redundant.

3.3 Local feature extraction: profile decomposition

When a dynamic object moves about in space, its movement parameters (velocity, acceleration, turning angle etc.) change over time. If we plot the evolution of a movement parameter over time, this will result in a profile or function, such as the one shown in Fig. 2. If we do this for different dynamic objects the resulting profiles will exhibit different amplitude and frequency   9variations, hence giving clues to the

underlying movement physics and behavior. This has lead us to using the movement
parameter profiles for extracting local features that could be used for trajectory
simulation and classification, by decomposing profiles into segments (or sections) of
'similar movement character'. We propose to use two measures for characterizing
movement from profiles: *Deviation* from the median line of the profile gives an
impression of the amplitude variation of a movement parameter over time, while
sinuosity acts as a proxy of the frequency variation. In the following, we describe the
computation of the deviation measure and the sinuosity measure that we use, as well as
the proposed algorithm for profile decomposition. Fig. 2 provides supporting graphical
illustrations and Algorithm 1 gives the pseudo-code of the profile decomposition
algorithm.

mp: movement parameter
(velocity, acceleration etc.)

res: deviation from median
bl: beeline
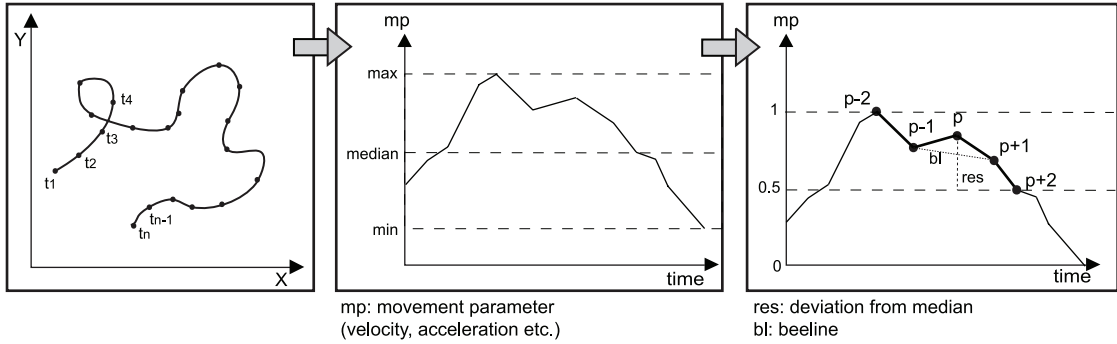
Fig. 2. Basic elements of movement parameter profiles

Both deviation and sinuosity are defined for each point on a movement parameter
profile. Before we compute these measures, we transform the profile data in the
following way. First, we calculate the median of the particular movement parameter that
was used to generate the profile. This median then can be seen to form a horizontal
'median line' that separates the movement parameter values into two halves. We then
take the residuals from the median for each point along the original profile. And finally,
in order to make the comparison across objects possible, we normalize all movement
parameter profiles to a common interval [0, 1], as shown, for instance, in Fig. 2.

The deviation of a point p on a profile is easily established: It simply equates to its
residual value from the median and has thus already been obtained when the residuals
were calculated above. The measure of sinuosity for p is computed as a ratio of the
distance $\pm k$ points along the profile to the length of the beeline connector centered at p,
as follows:

$$Sinuosity_{p,k} = \frac{\sum_{i=p-k}^{i=p+k-1} d_{i,i+1}}{d_{p-k,p+k}}$$

10

where k is the lag parameter. This method was originally introduced by Dutton (1999) in order to classify the sinuosity of cartographic lines in map generalization. After some experimentation, in order to obtain a more reliable measure for the sinuosity, we considered both 1 and 2 for k as the lag value. Then, the final sinuosity at p is computed as the average of the $Sinuosity_{p,1}$ and $Sinuosity_{p,2}$:

$$Sinuosity_p = \frac{\sum_{k=1}^{k=2} Sinuosity_{p,k}}{2}$$

The sinuosity measure ranges from 1 (if profile points are collinear about the given point p) to infinity for a winding profile (i.e. a space-filling curve). The sinuosity values for all points are then transformed to the interval [0, 1], as proposed by (Dutton 1999). Next, the profile points are classified into two regimes regarding the level of the corresponding sinuosity measure, '*low sinuosity*' and '*high sinuosity*', separated by a user-defined threshold. The same is done with deviation, where the standard deviation of the residuals is used to separate '*low deviation*' from '*high deviation*'. The described procedure is summarized in Algorithm 1.

Algorithm 1. Profile decomposition

Inputs:
- $res[]$: residuals from median
- st: threshold to distinguish low sinuosity from high sinuosity

Outputs:
- $decomX[]$: classified and decomposed profile

Algorithm:

```
01:      n ← the number of points on the profile
02:      dtime ← time interval between consecutive points
03:      for index of points i = 1 to n do
04:              dres ← res_{i+1} - res_i
05:              sl[i] ← sqrt(dtime² + dres²)
06:      end for
07:      dt ← standard deviation of res[]
08:      sinuosity[] ← 0
09:      for lag size k = 1 to 2 do
10:          for index of points i = (1+k) to (n-1-k) do
11:              beeline_distance ← length of beeline connector of p_{i-k} and p_{i+k}
12:              profile_distance ← Σsl of p_{i-k} to p_{i+k}
13:              sinuosity[i] ← profile_distance / beeline_distance + sinuosity[i]
14:          end for
15:      end for
16:      for index of points i = 1 to n do
17:      sinuosity[i] ← sinuosity[i] / 2
18:      sin_scaled ← scale sinuosity to the length of 1
19:      if (sin_scaled < st) AND (res[i] < dt) then decomX[i] ← 1          /* low sinuosity, low deviation
20:          elseif (sin_scaled >= st) AND (res[i] < dt) then decomX[i] ← 2     /* high sinuosity, low deviation
21:          elseif (sin_scaled < st) AND (res[i] >= dt) then decomX[i] ← 3     /* low sinuosity, high deviation
22:          elseif (sin_scaled >= st) AND (res[i] >= dt) then decomX[i] ← 4    /* high sinuosity, high deviation
23:      end if
24:      end for
25:      return decomX[]
```

The classified profile decomposes trajectory into the segments of homogeneous movement characteristics. The results of [11] employing the Algorithm 1 on different

movement parameter profiles (i.e. velocity, acceleration, etc.) can be used to compute local movement features for trajectory classification and simulation purpose.

4 Applications

We suggest that the above methodology, and in particular the trajectory decomposition algorithm, are useful for a variety of applications in movement data mining where finding similarities between the physical movement behavior of different objects is important. These include applications such as trajectory classification (e.g. transport mode detection in mobility analysis studies), movement pattern detection (e.g. fixation and saccade detection in eye-tracking research), and trajectory simulation (e.g. in human mobility behavior studies).

In the remainder of this Section, we introduce a procedure for trajectory classification. In the following Section 5, we examine the applicability of the proposed methods in a series of classification experiments using transportation data as well as in fixation detection in eye-tracking data.

4.1 Trajectory classification

We are trying to classify trajectories of moving objects in a systematic way using the features (i.e. variables) extracted by the trajectory decomposition algorithm described above. This procedure aims at classifying trajectory data generated by unknown moving objects and assigning them to known types of moving objects, whose movement characteristics have been previously extracted and learned. That is, we are assuming to use a supervised classification algorithm. We are interested to find out whether trajectories of different kinds of MPOs can be classified distinctively. The following subsections introduce our trajectory classification process as shown in Fig. 3, which consists of two main steps: 1) Feature selection (i.e. choosing the variables that provide the input to the classification process) and dimension reduction using principal component analysis; and 2) the actual classification using the support vector machine (SVM) classifier algorithm.
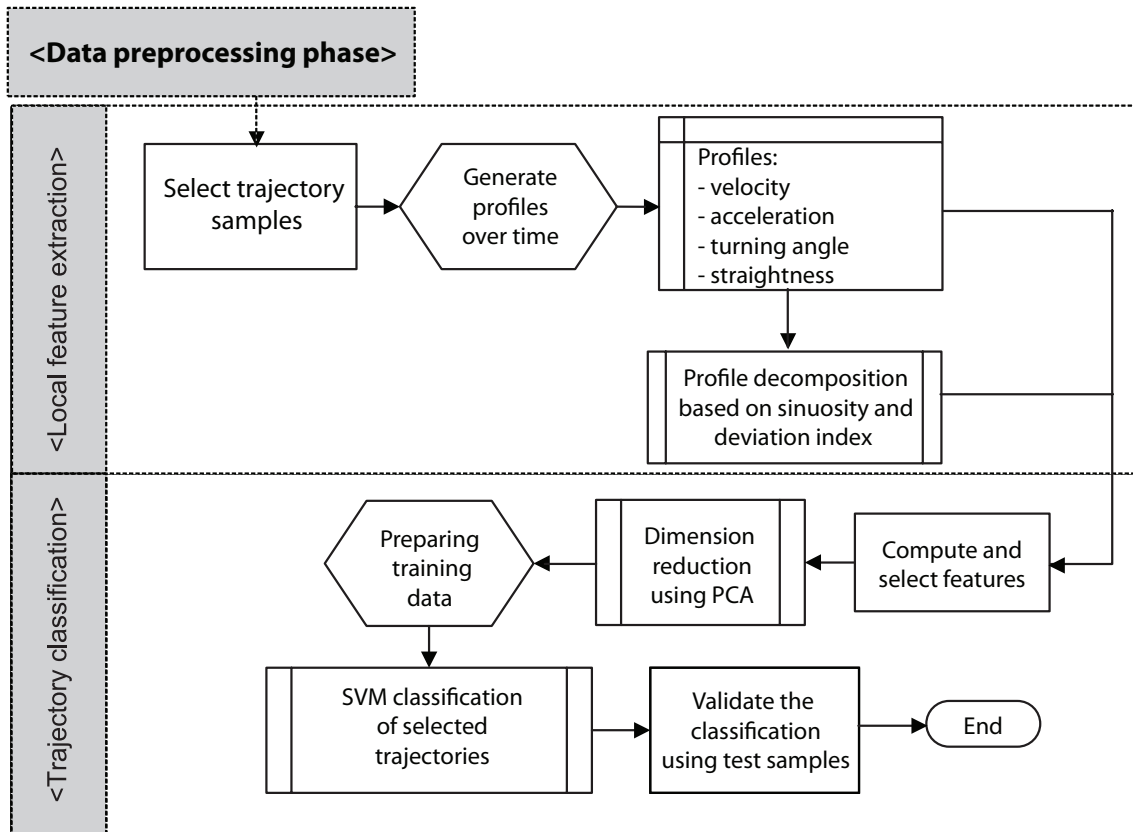
Fig. 3. Trajectory classification process

4.2 Feature selection and dimension reduction

A great number of global and local statistical descriptors can be computed for each trajectory. Each of these variables can potentially be selected as features for use in the classification process. However, as many of these features essentially describe similar characteristics, there are likely to exist correlations, suggesting that only a reduced set of features should in fact be used in the classification. Given the large number of global and local descriptors it would be very difficult to reduce the original set of features by correlation analysis, merely selecting a subset of the original features. Hence, we propose using principal component analysis (PCA) for reducing the number of original features, and hence dimensions in the feature space (Smith, 2002; Bozdogan, 2003; Guyon & Andre, 2006). PCA yields a (sub)set of synthetic, uncorrelated features called principal components, which contain the most important aspects of the original features.

4.3 Classification using SVM

The features that have been generated by the PCA for each MPO type are considered as a set of attribute categories that form the input for the final step of the classification

procedure. This step has the aim of classifying trajectories by assigning them to different types of moving objects. Essentially, we are interested in two aspects. First, we would like to see whether it is possible to tell apart, that is, to discriminate the trajectories generated by different types of moving objects based on the movement parameters that we have extracted from the trajectory data. Second, assuming that this is possible, we are interested in classifying dynamic objects of unknown type to the correct object type, that is, we would like to be able to reveal the identity of unknown objects. For instance, in transportation studies analysts are interested in detecting different modes of transport from unknown GPS trajectories of people.

Given the latter objective, it is advisable to use a supervised classification method where a training (or learning) stage is followed by a classification (or testing) stage that applies the learned discriminating functions to classify the unknown objects. In principle, any supervised classification technique could serve our purposes, but we chose to use the support vector machine (SVM) approach (Cristianini & Shawe-Taylor, 2000; Duda et al., 2001), which is widely used today in pattern recognition and data mining. The trajectory classification process then consists of the training stage where the SVM will learn from a set of trajectory samples (the training set) how to discriminate between MPO types by constructing separating hyperplanes in the multi-dimensional space formed by the input features; and a classification/testing stage that applies the learned hyperplanes on another set of trajectory samples (the testing set), thus predicting the object type of each of these unknown trajectories.

This step concludes our proposed overall methodology. After the SVM has been trained and validated, it is now ready for use in data mining operations to detect the MPO type of unknown dynamic objects from their trajectories. This could either take place off-line on large trajectory databases or in real-time.

5 Experiments: trajectory classification

In order to validate our methodology and demonstrate its applicability in the classification of trajectories of different MPOs, we have conducted a series of experiments that will be reported in this section and discussed in the next section. The experiments are designed to specifically investigate 1) automatic mode detection in transportation analysis and 2) feasibility study of using eye-tracking data as a proxy for other MPOs. For these experiments, we considered different types of MPOs with varying physics and behavior of movement, expressed through different movement parameters (Dodge et al., 2008). We have therefore selected different samples of

moving objects from both groups of dynamic objects introduced in Section 2. From the first group we have chosen movement data captured from pedestrians, bicycles, cars and motorcycles; from the second group we considered eye movement data. Among these data, bicycles, motorcycles, and cars and to a lesser degree pedestrian movements are typically constrained to the transportation network.

5.1 Experiments — objective

5.1.1 Automatic transport mode detection

Two experiments were designed to validate the applicability of the proposed methodology using a supervised classification technique, with the aim of automatically assigning the correct transport mode to trajectories of unknown objects, after training with a sample of known objects:

Experiment #1: Classification of objects of different speed range
   For this experiment, we acquired various trajectories from openstreetmap.org of known object sources from the transportation domain, including tracks of pedestrians, bicycles, cars and motorcycles. Fig. 4 illustrates the 2-D plot of exemplar trajectories generated by the four object types. For each object type about 50,000 GPS fixes from 10 trajectories remained after data cleaning, filtering and resampling to a temporal sampling rate of 1 second.
   Movements of different vehicles and pedestrians are performed at different ranges of speed. Therefore, classifying objects by simply taking the different speed range might seem as a straightforward solution. However, note that speed cannot be considered as the only parameter to classify objects in transportation since during rush hour all vehicles move at similar low speed. Therefore the proposed classification process takes variations and frequencies of changes of the other movement parameters (e.g. acceleration) into account, besides speed variations.
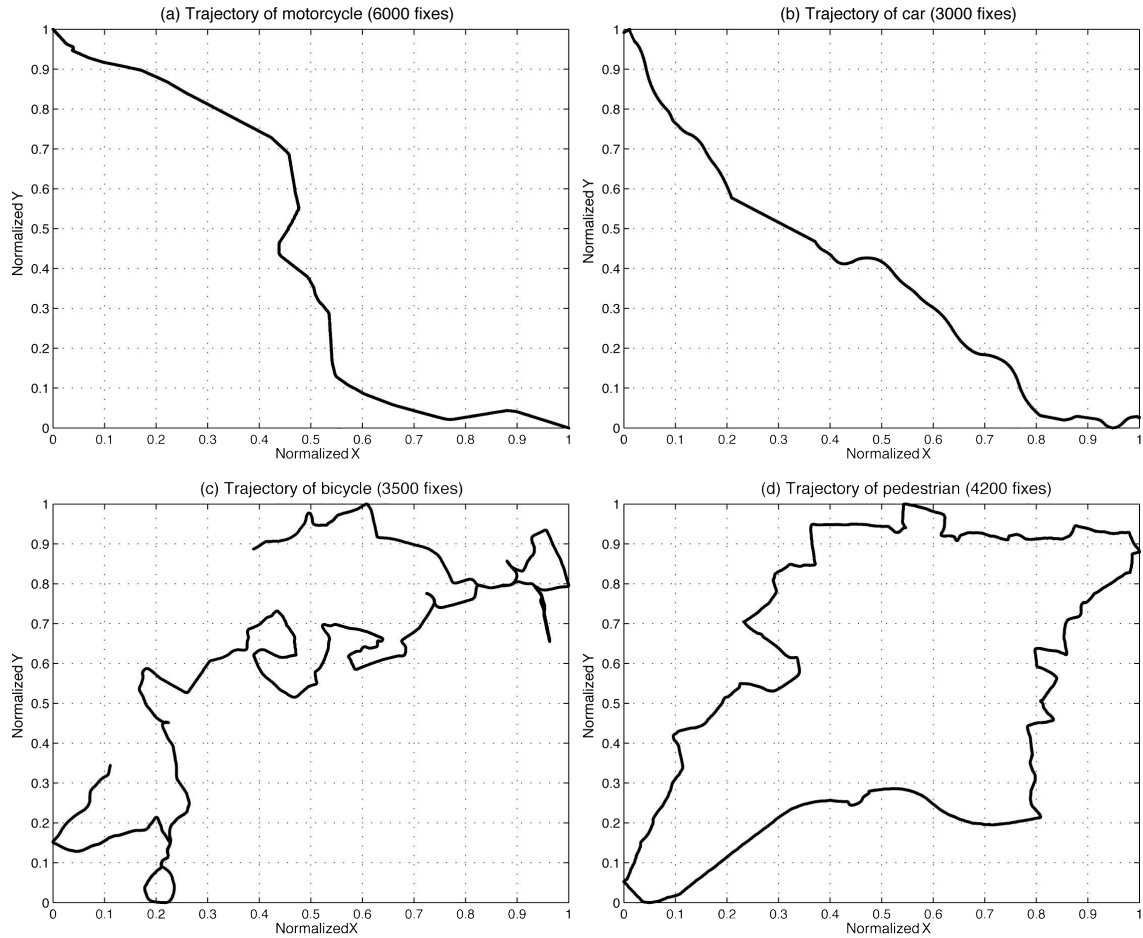
Fig. 4. Normalized trajectory data of exemplar moving objects

Experiment #2: Classification of objects of similar speed range

This experiment aims to investigate detecting the transport mode of trajectories collected from objects of similar speed range, exemplified by cars and motorcycles. As mentioned earlier, speed plays an important role in simulating and classifying trajectories representing different object types. However, when the speed range is similar it is indispensable to inspect distinct variations of other movement parameters such as acceleration and also examine speed variations at finer detail, in order to be able to differentiate between object types. Therefore, this experiment is intended to demonstrate that the proposed classification process is sufficiently subtle to be able to classify trajectories obtained from very similarly behaving objects.

5.1.2 Using eye-tracking data as a proxy of other MPOs

Experiment #3: classifying trajectories of eyes versus other object (non-eye)

With this experiment we aimed to assess ₁₆the suitability of eye-tracking data as a

proxy of other types of moving objects. For this experiment, similar to the previous experiments, we classified eye-tracking data collected from an eye-tracker against the data used in the first experiment. We intended to investigate whether it is possible to analytically tell apart trajectories generated by eye movement from those of other objects such as motorcycles, cars, bicycles and pedestrians that we subsume under the term "non-eye" objects. Specifically, we were interested to see whether it is feasible to use eye-tracking data in order to simulate other moving objects due to accessibility, privacy and data cost issues.

The eye movement data set used here (Fig. 5) was contributed by Arzu Çöltekin (Eye Movement Laboratory, Department of Geography, University of Zurich) and consists of about 50'000 gaze points from 2 eye movement trajectories captured by a Tobii eye tracker at an interval of 16 milliseconds during experiments on a 1600 x 1200 screen.
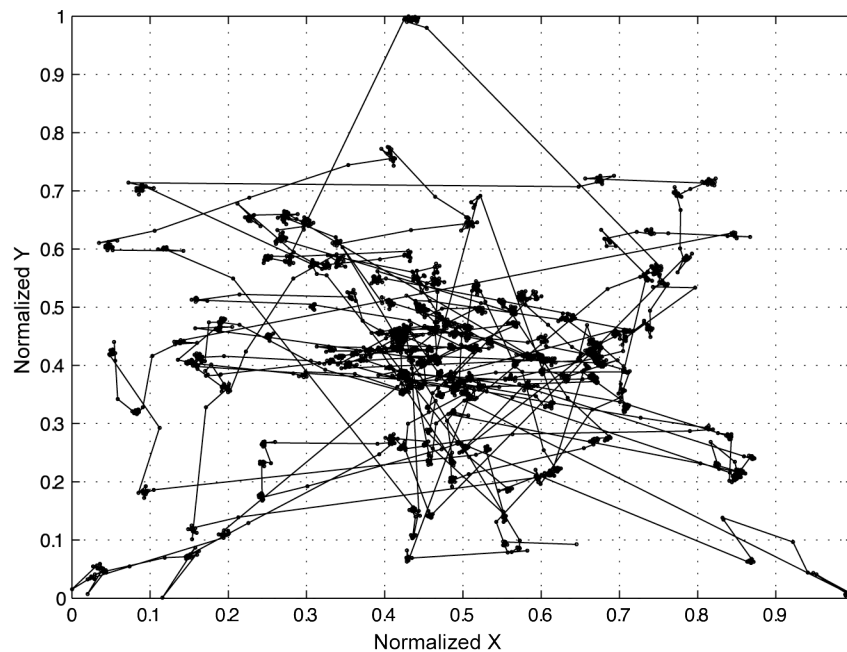
Fig. 5. Normalized sample trajectory of eye movement

5.2 Experiments — workflow

For the three experiments we pursued our proposed 3-step methodology described in section 3 followed by an additional phase of trajectory classification suggested in section 4.1. The workflow of the three experiments is described in the following subsection in more detail.

5.2.1 Trajectory data preparation

First, the raw movement data were ₁₇cleaned in order to remove outliers. In

the case of eye movement data, points that lay off the screen were considered as outliers and removed. The data were then resampled to a regular time interval, equal to the minimum sampling rate of the raw data (16 ms for eye movement data and 1 second for the other objects). In order to fill gaps linear interpolation was used, as the underlying movement geometry didn't suggest the use of a more elaborate interpolation technique. Finally, we applied moving average smoothing (window size of 5 sec) on the filtered, re-sampled data. For eye-movement data, only the filtering and resampling steps were applied. The reasons for not applying smoothing are the prevention of data loss and the potential creation of artifacts, as these types of trajectories exhibit a 'jagged' geometry that might be destroyed by the regularizing effect of trajectory smoothing. In the next step, from the entire dataset we selected our sample trajectories, each with a length of 300 points (i.e. with a duration of 5 mins for the transportation objects). All the sample trajectories were taken from various overland roads and were visually checked to be consistent and to largely homogeneous in terms of their path geometry to prevent artifacts in the results of the trajectory classification. However, in the case of eye-tracking data it is impossible to avoid having 'jagged' geometries, as described earlier. Finally, the selected sample trajectories served as input data for the experiments.

In our study, we initially experimented with two methods for smoothing of raw GPS data, Kalman filtering (Eubank, 2005) and moving average smoothing. Both methods yielded similar results for our data, seemingly contradicting the results reported in Jun et al (2007). However, the GPS data obtained from openstreetmap.org were captured by devices of unknown accuracy. Kalman filtering requires a model of movement, and not having solid knowledge available about the movement of the objects under study has probably seriously impacted on the performance of this smoothing method. Further experiments indicated that Kalman filtering does indeed generate superior results when more accurate data are available, confirming the findings of Jun et al (2007). Eventually, however, for reasons of practicability, we chose to use moving average smoothing, which is a reasonable smoothing method in the spatial domain.

5.2.2 Global descriptors

As mentioned before, Fig. 4 and Fig. 5 illustrate the 2-D plots of the trajectories of selected objects. From this figure it becomes obvious that the trajectory of the motorcycle (Fig. 4 a), car (Fig. 4 b), bicycle (Fig. 4 c), and pedestrian (Fig. 4 d), are much smoother than the trajectories of eye movement (Fig. 5). Of course, temporal granularity of the sampling will influence the smoothness and length of the traveled path. For instance, the overall character of   the car and motorcycle movement

captured every second appears smoother and closer to the pedestrian and bicycle movement. However, with a lower sampling rate (e.g. every hours) the trajectory of the car and motorcycle movement to some degree would be probably closer to the eye movement captured every few milliseconds. Table 1 to Table 3 present the descriptive statistics for the straightness index, velocity and displacement from the previous fix (or step length) as some examples of the movement parameters that were computed for the trajectories of the selected objects of Fig. 4 and Fig. 5.

MPO	Min	Max	Mean	Median	Stddev	Skewness
Motorcycle	1.42	1.60	1.5	1.5	0.02	0.52
Car	1.48	1.60	1.49	1.49	0.11	8.21
Bicycle	1.07	3.3	1.5	1.5	0.08	4.21
Pedestrian	1.03	5.8	1.5	1.5	0.16	14.40
Eye	1	3141.6	8.77	2.60	89.69	26.99

Table 1. Descriptive statistics for straightness index

MPO	Min	Max	Mean	Median	Stddev	Skewness
Motorcycle	0	35.13	31.12	32.8	4.94	-3.11
Car	0	33.49	33.03	31.04	3.13	-3.04
Bicycle	0	15	5.29	5.18	2.29	0.5
Pedestrian	0	2.5	1.65	1.68	0.29	-1.97
Eye	0	20	1.18	0.48	2.36	4.13

Table 2. Descriptive statistics for velocity (eyes: [pixel/ms], other MPOs: [m/s])

MPO	Min	Max	Mean	Median	Stddev	Skewness
Motorcycle	0	34.08	29.34	32.18	6.52	-1.94
Car	0	32.83	29.39	30.75	3.88	-2.77
Bicycle	0	17	3.34	2.69	2.48	3.34
Pedestrian	0	2.2	1.17	1.26	0.4	1.17
Eye	0	950	15.29	4.63	46.46	15.29

Table 3. Descriptive statistics for displacement from the previous state

(eyes: [pixel], and othe MPOs [m])

5.2.3 Correlation analysis

For the four selected MPOs, Table 4 presents the results for the Spearman rank correlation coefficients for different pairs of movement variables. The straightness index is not used because it is a compound index using displacement. The results suggest a strong positive correlation between velocity and displacement from the previous fix for all studied objects. Moreover, there is no correlation identified between acceleration and turning angle for the selected objects. Outcomes show a negative weak correlation between velocity and turning angle for car, motorcycle, pedestrian and bicycle movement. However, for eye movement almost no correlation occurs (Table 4).

Correlation	Motorcycle	Car	Bicycle	Pedestrian	Eye
Velocity - acceleration	0.065	0.016	0.07	0.23	0.36
Velocity - turning angle	-0.38	-0.25	-0.25	-0.13	-0.06
Velocity - displacement	0.99	1	1	1	0.99
Acceleration - turning angle	-0.1	0.002	0.02	0.01	0.06
Acceleration - displacement	0.065	0.016	0.07	0.23	0.36
Displacement - turning angle	0.38	-0.25	0.25	-0.12	0.06

Table 4. Spearman Rank Correlation coefficients

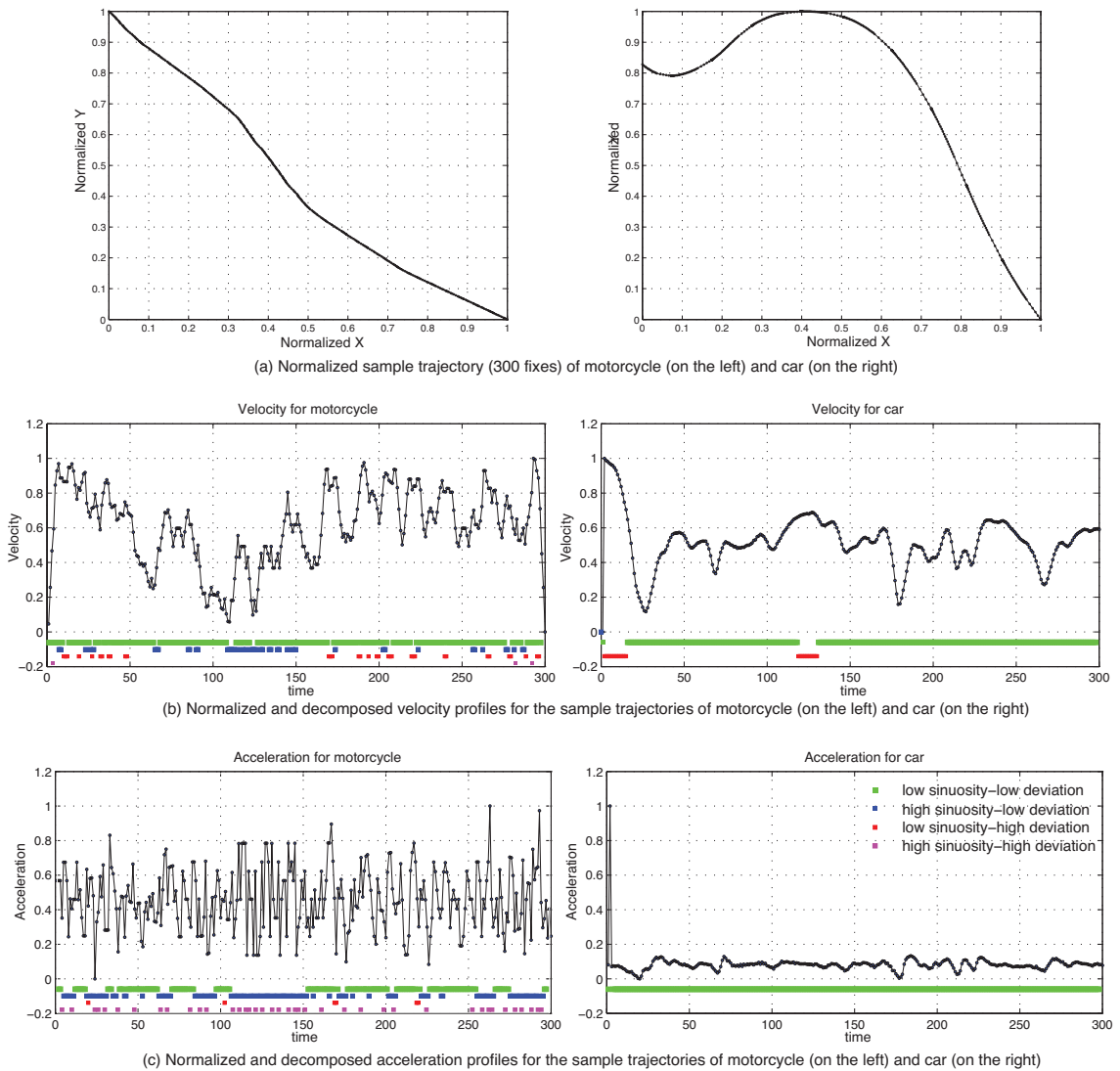### 5.2.4 Locally extracted features

We generated movement parameter profiles for velocity, acceleration, turning angle, and straightness index for our trajectory data. Using Algorithm 1 we then decomposed the profiles into the four classes foreseen in the algorithm. After some initial experiments, we found threshold values that yielded consistent results over all trajectory samples. For sinuosity, we have set the threshold separating low from high sinuosity at 0.95. For deviation, we use the standard deviation of the residuals of a particular profile.

The results of the decomposition of the movement parameter profiles for four of the trajectory samples are depicted in Fig. 6 and Fig. 7. Fig. 6 illustrates the results of the decomposition process on a sample trajectory of a motorcycle on the left and a sample trajectory of a car on the right (from experiments #1 and #2). Similarly, Fig. 7 shows the results of the decomposition process on a sample trajectory of a bicycle on the left and a sample trajectory of eye movement on the right (from experiment #3). In order to save space, we do not visualize the sample result of the decomposition of a pedestrian trajectory, which looks very similar to the result for the bicycle trajectory. However, as mentioned earlier trajectory samples of pedestrians have been included in

experiments #1 and #3. The individual graphs in Figures 6 and 7 represent the normalized profiles of velocity (Fig. 6.b and Fig. 7.b) and acceleration (Fig. 6.c and Fig. 7.c), respectively. At the bottom of each graph the four decomposition classes are shown as follows:

- Green: low sinuosity – low deviation
- Blue: high sinuosity – low deviation
- Red: low sinuosity – high deviation
- Magenta: high sinuosity – high deviation

The above results form the input for the remaining steps and will be discussed in Section 6.

(a) Normalized sample trajectory (300 fixes) of motorcycle (on the left) and car (on the right)

(b) Normalized and decomposed velocity profiles for the sample trajectories of motorcycle (on the left) and car (on the right)

(c) Normalized and decomposed acceleration profiles for the sample trajectories of motorcycle (on the left) and car (on the right)

Fig. 6. Normalized and decomposed velocity and acceleration profiles for the sample trajectories of motorcycle and car

(a) Normalized sample trajectory (300 fixes) of bicycle (on the left) and eye movement (on the right)

(b) Normalized and decomposed velocity profiles for the sample trajectories of bicycle (on the left) and eye movement (on the right)

(c) Normalized and decomposed acceleration profiles for the sample trajectories of bicycle (on the left) and eye movement (on the right)
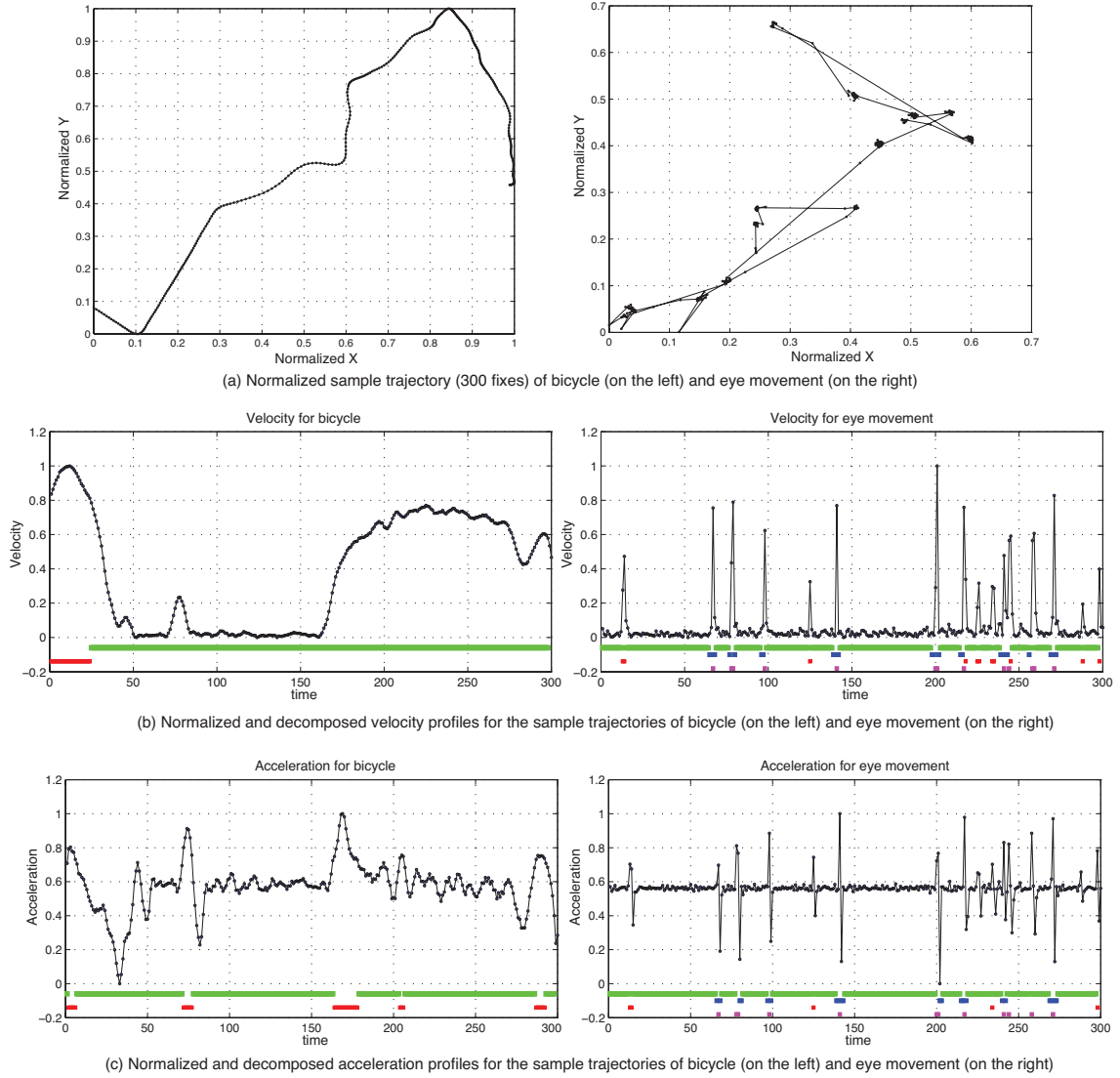
**Fig. 7. Normalized and decomposed velocity and acceleration profiles for the sample trajectories of bicycle and eye movement**

5.2.5 *Feature selection and PCA*

In our experiments, we selected a total set of 58 features from the movement parameters previously extracted on the global and local level from the trajectories, as summarized in Table 5. Following the correlation analysis conducted previously, we excluded displacement from the selection of features, as it correlates highly with velocity. From the global parameters, we further excluded turning angle, because it does not help to differentiate between objects. Consequently, we used three movement parameters (i.e. straightness index, velocity, and acceleration) to compute the mean and standard deviation at the global level, resulting in 6 selected global features (Table 5, top row).

22

	Descriptors	# of descriptors
Global	Mean and stddev at global level, per movement parameter (3)	6
Local	Mean and stddev of segment length, per decomposition class (4), per movement parameter (4)	32
	Number of decomposition class changes, per movement parameter (4)	4
	Percentage of each decomposition class (4), per movement parameter (4)	16

Table 5. Original features selected for the classification

(a) Experiment #1

(b) Experiment #2

(c) Experiment #3
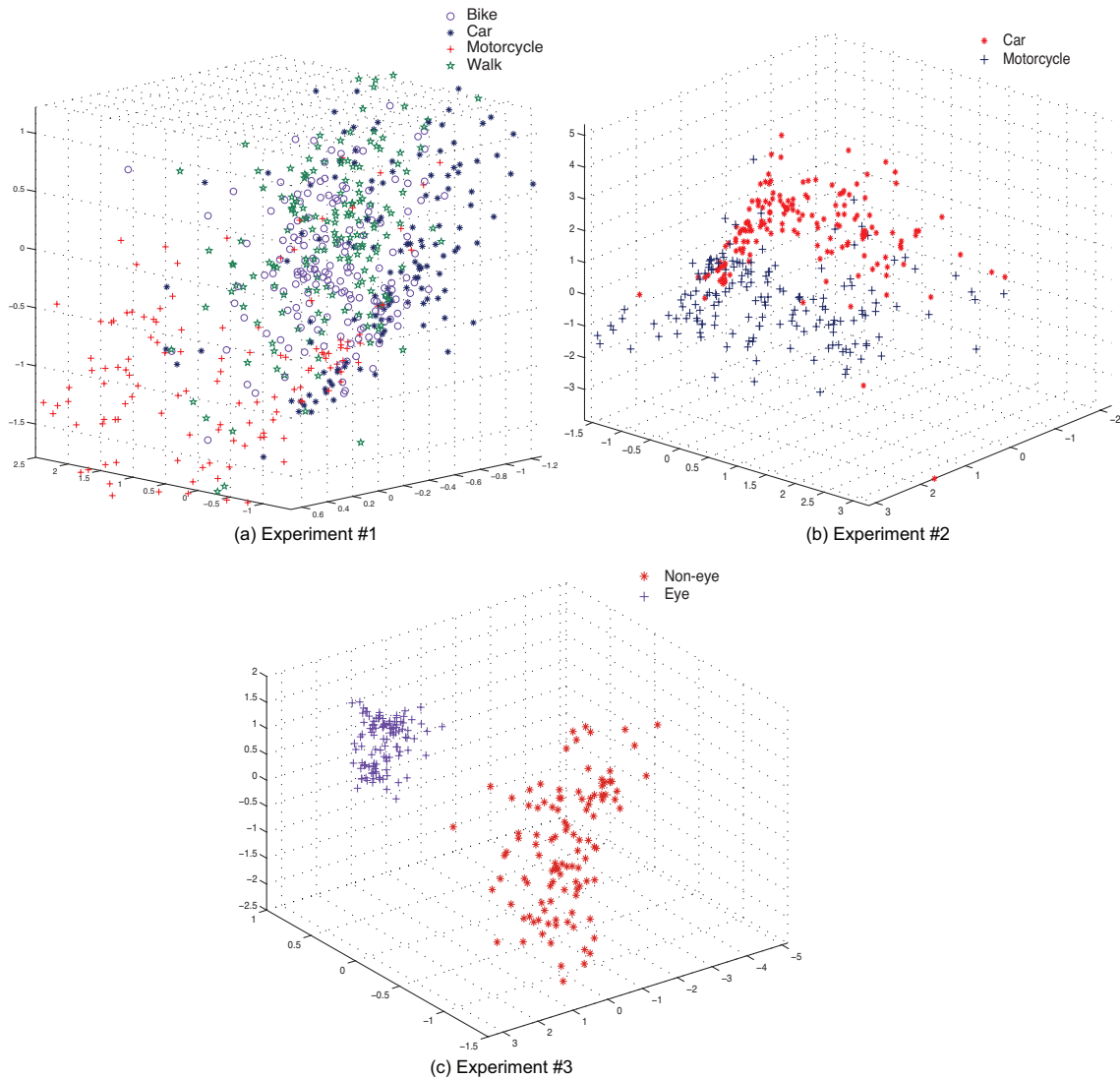
Fig. 8. 3-D plot of the first three principal components of the sample trajectories

The set of local features obtained from the four movement parameter profiles shown in section 5.2.4 is made up of the mean and standard deviation of the segment length per decomposition class and per descriptor (resulting in 32 features); the number of changes of decomposition classes along the profile, computed for each descriptor (4 features); and the percentage that each $_{23}$decomposition class holds from the total

number of points, per descriptor (16 features).

The above selected 58 features were input to a PCA to form uncorrelated linear combinations of the original features. Consequently, the number of features was reduced to 15 principal components for experiments #1 and #2 and 11 principal components for experiment #3, which formed the input for the trajectory classification step. Fig. 8 visualizes the 3-D plots of the first three principal components for the sample trajectories of the different objects used in these three experiments.

5.3 Experiments — results

For the classification stage of the proposed methodology, we randomly selected 165 samples of stretches consisting of 300 points from the various trajectories introduced in section 5.1. 115 samples from eye movement trajectories, 165 from motorcycle trajectories, 165 from car trajectories, 165 from bicycle trajectories, and 165 from pedestrian trajectories. We then ran the decomposition algorithm for all the samples to compute the corresponding global and local movement properties. Three experiments were then conducted to evaluate the trajectory classification procedure.

The main objective of experiments #1 and #2 was to evaluate whether the proposed methodology could be applied in automatic detection of transportation mode. For experiment #1, we used 560 trajectory samples from the four pools of motorcycle, car, pedestrian and bicycle trajectories as a training set for SVM learning (i.e. 4 x 140 samples). The remaining 100 samples from the four pools (i.e. 4 x 25 samples) were used as a testing set to evaluate the performance of the classification. The aim of this experiment was to evaluate how well the different types of transportation MPOs could be differentiated using the proposed methodology in a multi-class classification mode. Conversely, experiment #2 had the objective of assessing a two-class classification. For this experiment, we used 280 trajectory samples from the two pools of motorcycle and car trajectories as a training set for SVM learning (i.e. 2 x 140 samples). The remaining 50 samples from the two pools (i.e. 2 x 25 samples) were used as a testing set to evaluate the performance of the classification. More specifically, in this experiment we intended to assess how well trajectories of motorcycles and cars, as exemplars of MPOs of similar speed range, could be differentiated.

Finally, the intention of experiment #3 was to evaluate how similar (or different) trajectories generated by eye movement are from trajectories of non-eye objects from the transportation domain (i.e. motorcycles, cars, bicycles, and pedestrian) using the proposed methodology in a multi-class   classification mode. Consequently, we

ran the SVM learning process with a training set consisting of 90 eye movement trajectories and 90 non-eye movement trajectories (i.e. 25 motorcycle, 25 car, 20 pedestrian and 20 bicycle trajectories). We tested the classification performance using a testing set of 25 eye movement trajectory samples, together with 25 non-eye movement trajectory samples (i.e. 7 motorcycle, 8 car, 5 bicycle, 5 pedestrian).

Experiment	Object	# train traj.	# test traj.	# correct class	Error of commission	Error of omission	Kappa coefficient	% Correct class
Exp. #1	motorcycle	140	25	23	0.041	0.08	0.76	82%
	car	140	25	21	0.043	0.12		
	bicycle	140	25	19	0.34	0.24		
	pedestrian	140	25	18	0.25	0.28		
Exp. #2	motorcycle	140	25	23	0.042	0.08	0.88	94%
	car	140	25	24	0.077	0.04		

Table 6. Results of the SVM classification for the experiments #1 and #2

In order to perform the experiments, we used the LIBSVM tool (Chang & Lin, 2001). We applied a radial basis function (RBF) kernel with two parameters: $c = 2$, which is a penalty function for misclassified sample points of training data; and $\gamma = 0.07$, which is an exponent factor in the RBF function (Cristianini & Shawe-Taylor, 2000). They were obtained by trying out different parameter combinations and evaluating the classification accuracy by means of cross-validation. The results of experiments #1 and #2 are presented in Table 6. From experiment #3, we achieved a classification accuracy of 100% cleanly separating all eye movement trajectories from the non-eye trajectories used in this study. Thus, we refrain from presenting this result in a table.

6 Discussion

In this section we discuss the results presented in the previous section. We first compare the characteristics of the 2-D trajectories as well as their associated movement parameters expressed in the profiles, then discuss the results of the three classification experiments, and finally take a brief look at efficiency considerations.

6.1 Global and local movement descriptors

Trajectories

Not surprisingly, the descriptive statistics of the straightness index and the 2-D plots

of the trajectories (Table 1, Fig. 4, Fig. 5) as well as the straightness index profiles for the trajectory samples suggest that the car movement with a mean straightness index value of 1.49 and standard deviation close to 0.11 represents the smoothest movements, while eye movement is the most unsteady movement, with a mean straightness index value of 8.77 and a standard deviation of 89.69.

The 2-D plots of the exemplar motorcycle, car, bicycle and pedestrian trajectories (Fig. 4) suggest that the geometry of such objects with a sampling rate of one second to some extent is comparable to each other. However, from the further numerical analysis and systematic classification that we have done in experiments #1 and #2, it can be concluded that these four moving objects behave differently in terms of the velocity, acceleration and straightness index of their paths (Table 1 to Table 3; and Fig. 6 and Fig. 7, left side).

Velocity

As Fig. 6.b, Fig. 7.b and Table 7 show, the velocity of cars, bicycles and pedestrians lies in two classes of high (above 90%) and low (less than 10%) deviation from the median, always with low sinuosity. On the other hand, the velocity profile of motorcycle movement changes between all four decomposition classes. It mostly lies in two classes of high (72.48 %) and low (15.1%) sinuosity, with low deviation from the median. This means that velocity undulates very closely around the median and does generally not deviate greatly from the trajectory (i.e. only 5.37% of profile points are classified as high deviation). The results indicate that the velocity profiles of the bicycles and pedestrians have the least variations between classes and the highest proportion of low sinuosity-low deviation points. However, the velocity profiles of the motorcycle, car, bicycle and pedestrian trajectories have some small perturbations that can be attributed to the limited accuracy of the GPS and random noise. In comparison, the profile of eye movement velocity suddenly increases at certain points (Fig. 7.b on the right) when a saccade (i.e. rapid movement of the eyes) happens, although it stays close to the median (like the pedestrian movement) for the remaining part of the profile at fixation points, where the eyes fixate (Salvucci, 2000). This points to the potential of using our approach to detect fixations and saccades from eye-movement protocols. As shown in Fig. 9, long segments of low deviation indicating fixations can be nicely extracted from short segments of high sinuosity-high deviation with a length of only 1 or 2 points in saccades. This behavior is distinctly different from the velocity variation of the other objects under study.

			low sinuosity – low deviation			high sinuosity – low deviation			low sinuosity – high deviation			high sinuosity – high deviation		
Obj#	Mean	Stddev	% class	Mean length	Stddev length	% class	Mean length	Stddev length	% class	Mean length	Stddev length	% class	Mean length	Stddev length
Motorcycle	28.73	6.91	72.48	7.85	6.41	15.1	2.31	0.95	5.37	2.23	0.43	1	1.67	0.58
Car	10.95	3.07	91.27	90.67	84.18	0	0	0	8.72	13	1.41	0	0	0
Bicycle	4.56	3.88	91.94	274	0	0	0	0	8.05	24	0	0	0	0
Pedestrian	3.25	0.56	97.65	97	127.47	0	0	0	2.34	3.5	2.12	0	0	0
Eye	308.34	617.03	73.87	7.42	6.80	17.59	3.18	1.40	0	0	0	8.54	2	0

Table 7. Summary table of the velocity profile decomposition of the sample trajectories
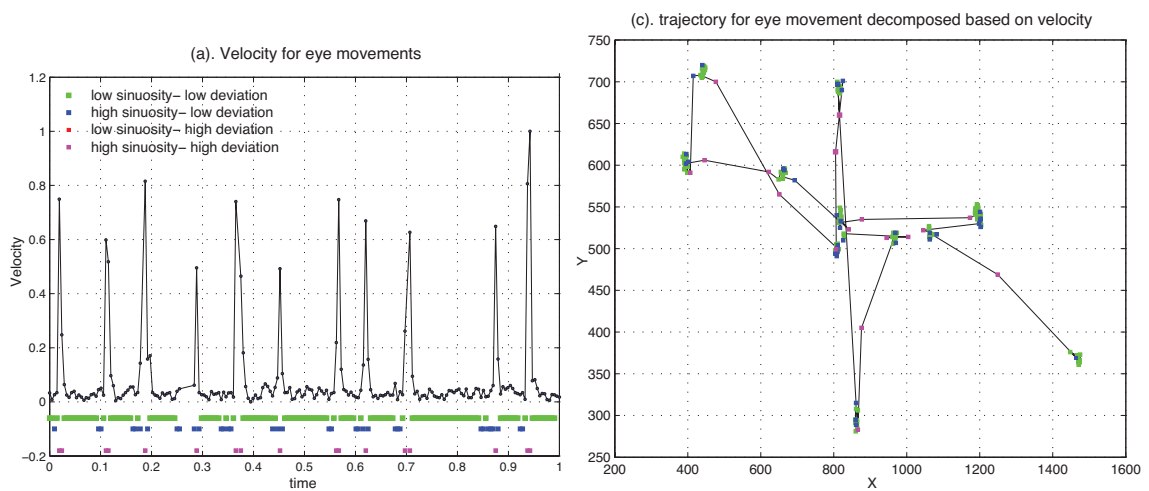

Fig. 9. Extracting saccades and fixations from trajectories of eye movement

Acceleration

In terms of the profile decomposition classes, the acceleration profiles of the five objects share similarities with the corresponding velocity profiles (Fig. 6, Fig. 7, Table 8). For instance, the acceleration profile of cars (and similarly for bicycles and the pedestrians) mostly varies very close to its median, with only 0.33% of points showing a higher deviation. All profiles show a higher proportion of high sinuosity-low deviation points than the corresponding velocity profiles. In the case of motorcycle, car, bicycle and pedestrian movement, there are some small perturbations that cause higher sinuosity on the corresponding acceleration profiles, which are due to the accuracy of the GPS devices used as well as random noise. This noise could be removed by curve fitting to profiles (instead of simply smoothing the trajectories). In the case of the eye movement and motorcycle movement, it is interesting to see that despite the noise, the high sinuosity-high deviation points are also picked up in the acceleration profiles. For eye movement, the match is even perfect; some segments are slightly shorter but they

27

all occur at the same spot as in the velocity profiles. Therefore, as stated earlier, the proposed segmentation algorithm can be employed successfully on velocity and acceleration profiles of eye movement trajectories as a fixation detection method. The acceleration profile of the motorcycle movement shows longer periods of high deviation than the eye movement and a more intermittent pattern of changes between the four different decomposition classes than any other profile (Fig. 6 b).

Obj#	Mean	Stddev	low sinuosity – low deviation			high sinuosity – low deviation			low sinuosity – high deviation			high sinuosity – high deviation		
			% class	Mean length	Stddev length	% class	Mean length	Stddev length	% class	Mean length	Stddev length	% class	Mean length	Stddev length
Motorcycle	0.002	7.4	45.97	8.68	6.45	38.59	6.67	8.05	2.01	1.75	0.5	13.42	1.97	0.16
Car	0.04	1.3	99.32	148	207.89	0.33	1	0	0.33	1	0	0	0	0
Bicycle	0.01	0.22	88.59	52.8	46.67	0	0	0	11.4	4.5	3.25	0	0	0
Pedestrian	0	0.14	90.60	38.57	34.85	0.67	1.5	0.7	8.39	4.16	1.6	0.33	1	0
Eye	-0.44	41.15	70.35	7.68	6.64	23.62	2.52	1.34	0.50	1	0	5.52	1.9	0.32

Table 8. Summary table of the acceleration profile decomposition of the sample trajectories

Straightness index and turning angle

The decomposition results for the straightness index profiles are not shown graphically, in order to save space. A summary of decomposition classes is given in Table 9. The results indicate that motorcycle, car, bicycle and pedestrian movement are very smooth, with about 98 % of the profile points assigned to the low sinuosity class. In the case of cars, bicycles and pedestrians the profile mostly stays close to the median (about 98 % in the high deviation class). However, the motorcycle profiles lie in 10 % of the cases in the high deviation class. In contrast, from the decomposition results it is obvious that the path of eye movement trajectories is more sinuous.

By the same token, the decomposition results of the turning angle profiles (not shown here to save space) demonstrated that the turning angle profiles of eye movement are very rough and exhibit an irregular, almost violent behavior, in contrast to the turning angle profiles of the other objects.

Obj#	Mean	Stddev	low sinuosity – low deviation			high sinuosity – low deviation			low sinuosity – high deviation			high sinuosity – high deviation		
			% class	Mean length	Stddev length	% class	Mean length	Stddev length	% class	Mean length	Stddev length	% class	Mean length	Stddev length
Motorcycle	1.5	0.2	89.26	53.2	56.66	0.33	1	0	10.4	2	0	0	0	0
Car	1.5	0.15	97.99	97.67	88.99	0.67	2	0	1.34	2	1.41	0	0	0
Bicycle	1.48	0.18	96.64	96	61.73	2.01	3	1.41	0.33	1	0	1	1.67	0.58
Pedestrian	1.49	0.16	96.98	96.33	87.75	0.33	1	0	2.68	4	1.41	0	0	0
Eye	5.32	9.27	54.27	5.27	4.15	35.17	3.71	2.55	0.5	1	0	10.05	1.94	0.23

Table 9. Summary table of the straightness index profile decomposition of the sample trajectories

6.2 Trajectory classification

For experiment #1, the multi-class classification of motorcycle, car, bicycle and pedestrian trajectories, we achieved an overall accuracy of 82 % and a Kappa coefficient of 0.76 (Table 6). One of the motorcycle sample trajectories was classified as a car trajectory and another one was classified as a bicycle trajectory. The same happened in the case of car movements (3 misclassifications). The other misclassifications were due to pedestrian trajectories classified as bicycle trajectories, and vice-versa. As the discussion of movement parameter profiles above shows, these misclassifications were due to the fact that motorcycle and car movements on the one hand, and bicycle and pedestrian movements on the other hand, are indeed quite similar. The two confusions of motorcycle trajectories with a bicycle and a car, respectively, were related to movement samples at lower speed.

For experiment #2, the motorcycle vs. car classification, we reached an overall accuracy of 94% and a Kappa coefficient of 0.88 (Table 6). One car movement sample was classified as motorcycle, and two motorcycle samples classified as car. These misclassifications were again due to the fact that these particular samples happened to fall into an extended period of low speed movement.

For experiment #3, the eye vs. non-eye classification, we achieved an overall accuracy of 100 %. This is clearly due to the fact that the non-eye MPOs used in this experiment are lacking the typical saccadic movement patterns of eyes. Hence, we can conclude that generating movement parameters similar to those of other moving objects is not possible using eye movement data, and hence eye movement data are not suitable as a proxy of other movement data that are examined in this study.

The above findings are further illustrated in Fig. 8, which shows a 3-D plot of the first three principal components computed on the trajectory samples used in the three

experiments. Fig 8.a shows how the bicycle and the pedestrian samples take the middle ground between the car and the motorcycle movement samples. Fig 8.b illustrates the separation of the car and the motorcycle movement samples. Fig 8.c then illustrates how the eye movement samples clearly stay apart from the non-eye movement observations (motorcycle, car, bicycle and pedestrian samples).

From the outcomes of the experiments it can be concluded that the amplitude and variation of velocity and acceleration are the most essential features in recognizing a certain travel mode or object type. For instance, the following rules, which can also be discovered from Fig. 6 and Fig. 7, are learned by the SVM to classify the trajectories: If the velocity and acceleration profiles are rather smooth and mostly composed of low sinuosity-low deviation segments, then the profile may belong to a trajectory of a car or bicycle. If the velocity and acceleration profiles contain a number of points with high sinuosity, then they may belong to a motorcycle trajectory. If the velocity and acceleration profiles have a jagged geometry consisting of a set of low sinuosity-low deviation segments interrupted by a set of high sinuosity-high deviation points, then the profiles are indicating the saccadic movement of eyes.

6.3 Efficiency

In order to be useful for data mining our proposed methodology has to be reasonably efficient for massive databases or for real-time applications. Due to lack of a large trajectory database it was not possible to empirically assess the computational performance of our methodology under these conditions. Nevertheless, we would like to briefly touch on efficiency issues here in order to support the argument that our methodology indeed has the potential to be used with massive datasets or in a real-time setting.

First, all parts of the methodology including the profile decomposition algorithm run in linear time, except the PCA and the SVM classification. Second, the training stage of the SVM classifier, which is known to have slow computational performance, is run offline and on a subset of the data. And finally, it is possible to replace the PCA and the SVM classifier by simpler and computationally more efficient techniques.

6.4 Test data used

The test data sets used are relatively large: 660 (4 x 165) transportation tracks for experiments #1 and #2, and another 115 eye movement tracks for experiment #3. We believe our experiments to be sufficient to 30establish the *feasibility* of the proposed

methodology. However, the test data are restricted to movement on overland and suburban roads (i.e., no urban traffic included) and they were originally sampled at a similar temporal interval (around 1 sec.). In order to make conclusive statements about the *scope of applicability* of the proposed methodology, the experiments would have to be extended to data sets of very different moving objects; to traffic movement in urban situations; and possibly to data that have been sampled at different temporal resolutions and may contain gaps.

While such experiments still need to be carried out, we expect that the methodology should be capable of handling tracks with different transportation modes due to the decomposition of trajectories into segments of homogenous character based on change points (Zheng et al., 2008). Also, the decomposition algorithm used is based on simple principles and does not use any extra knowledge, which is why we expect it to be robust also for different moving object types. The performance of the decomposition, and thus of the overall methodology, might decrease for very short trajectories or tracks with similar movement parameters, for instance in congested traffic situations. However, by considering the history of the entire trajectories, such track sections may be classified more accurately. For instance, knowing the velocity characteristics in uncongested parts of the trajectories involved in a congestion, bicycles may be distinguished from cars or motorcycles.

7   Conclusions

We have presented a comprehensive, three-stage methodology that allows extracting movement parameters from the trajectories of different types of moving objects. As one of the application of the proposed methodology, we showed how to classify trajectories of unknown MPOs by similarity to the trajectories of previously learned MPOs. We have then conducted a series of experiments that not only demonstrated the feasibility of the proposed methodology but also provided interesting empirical results. Our experiments provide evidence about the similarities and differences that exist among different types of moving objects in the transportation domain. The results show that using our methodology we can successfully detect the mode of transport from unknown trajectories of people using different transportation means. It was also shown that eye movement data cannot be successfully used as a proxy of full-body movement of humans, or vehicles. The physics of movement of virtually mass-less movement processes, such as eye movement (and possibly also computer mouse movement), is very different from the movement of objects that are governed by inertia to a much greater extent. Nevertheless, the ₃₁methodology can contribute to finding

the most feasible proxies for desired moving objects in various application domains (e.g. biology, ecology). For instance, eye movement could potentially be considered a proxy of some objects that have a stop-and-go movement behavior such as bees and butterflies.

We see potential for future work in three directions. First, there is plenty of room for more experiments aiming to further exploit, enhance and consolidate the proposed methodology. For instance, experiments with different trajectory datasets; other MPO types; different transportation data (e.g. movement on urban roads); different sets of movement parameters; fine-tuning of the SVM classifier (e.g. kernel tuning); and other classification techniques (e.g. decision trees). Since we have set up the methodology in a streamlined, automated process, we are in a good position to conduct such further experiments. From the point of view of real-time processing, experiments with a simpler classifier than SVM, which is known to have a high computational complexity, may be warranted. Finally, the proposed methodology could be developed further to set up an automatic transport mode detection system in transportation applications.

Second, we are interested in further exploring the method and results of movement parameter profile decomposition. For instance, as we discussed in section 6.1, we believe that there is a potential in using the decomposition algorithm as an alternative technique for fixation detection in the analysis of eye tracking data. Also, we are interested in using the results of the profile decomposition algorithm for trajectory similarity analysis as well as for more differentiated parameterization of movement simulators.

Third, our methodology currently does not take into account the context and constraints that influence movement. Further studies therefore have to consider how to involve movement context.

Acknowledgement

References

Agouris, P., Partsinevelos, P., Stefanidis, A.. (2003). Differentiating and Modeling Multiple Moving Objects in Motion Imagery Datasets. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XXXIV-5/W10

Bashir, F.I. and Khokhar, A.A. and Schonfeld, D. (2007). Object Trajectory-Based Activity Classification and Recognition Using Hidden Markov Models. *IEEE Transactions on Image Processing*, 16(7), 1912-1919.

Batty, M., (2003). Agent-Based Pedestrian Modelling. Working paper. Centre for Advanced Spatial Analysis, University College London. UK. ISSN: 1467-1298.

Bay, S., and Pazzani, M., (2001). Detecting Group Differences: Mining Contrast Sets. *Data Mining and Knowledge Discovery*, 5(3), 213-246

Benhamou, S. (2004). How to Reliably Estimate the Tortuosity of an Animal's Path: Straightness, Sinuosity, or Fractal Dimension? *Journal of Theoretical Biology*, 229, 209–220.

Blythe, P.W., Miller, G.F. & Todd, P.M. (1996). Human Simulation of Adaptive Behavior: Interactive Studies of Pursuit, Evasion, Courtship, Fighting, and Play. *Proceedings of the Fourth International Conference on Simulation of Adaptive Behavior*, Cambridge, MA: MIT Press/Bradford Books, 13-22.

Bozdogan, H. (2003). *Statistical Data Mining and Knowledge Discovery*. CRC Press, Inc.

Brillinger, D. R., Preisler, H. K., Ager, A. A., and Kie, J. G. (2004). An exploratory data analysis (EDA) of the paths of moving animals. *Journal of Statistical Planning and Inference*, 122(1-2), 43-63.

Chatfield, C. (1989). *The Analysis of Time Series: An Introduction*. Fourth edition. London, UK: Chapman and Hall.

Chang C.-C. and Lin C.-J. (2001). LIBSVM: a library for support vector machines. Software available at http://www.csie.ntu.edu.tw/~cjlin/libsvm

Chen, L., Özsu, M. T. & Oria, V. (2005). Robust and Fast Similarity Search for Moving Object Trajectories. *Proceedings of the ACM SIGMOD International Conference on Management of Data*, ACM. 491-502.

Chen, M.C., Anderson, J.R, and Sohn, M.H. (2001). What Can a Mouse Cursor Tell Us More? Correlation of Eye/Mouse Movements on Web Browsing. *Proceedings of the ACM Conference on Human Factors in Computing Systems (CHI'01)*. Seattle, Washington, USA..281–282.

Cox, A.L. and Silva, M.M. (2006). The Role of Mouse Movements in Interactive Search. *Proceedings of the 28th Annual CogSci Conference*, Vancouver, Canada. 1156–1162.

Cristianini, N. and Shawe-Taylor, J. (2000). *An Introduction to Support Vector Machines and other Kernel-based Learning Methods*. Cambridge: Cambridge University Press.

Dodge, S., Weibel, R. & Lautenschütz, A.-K. (2008). Towards a Taxonomy of Movement Patterns. *Information Visualization*. doi:10.1057/palgrave.ivs.9500182.

Duda, R.O., Hart, P.E., Stork, D.G. (2001). *Pattern Classification*. New York et al.: John Wiley & Sons, Inc.

Dutton, G., (1999b). Scale, Sinuosity, and Point Selection in Digital Line Generalization. *Cartography and Geographic Information Science*, 26, 33-53.

Eubank, R. (2005). A Kalman Filter Primer (Statistics: Textbooks and Monographs). Chapman & Hall/CRC.

Giannotti, F. & Pedreschi, D. (eds.) (2007). *Mobility, Data Mining and Privacy – Geographic Knowledge Discovery*. Berlin Heidelberg: Springer-Verlag.

González, M. C., Hidalgo, C. A. & Barabási, A-L. (2008). Understanding Individual Human Mobility Patterns. *Nature*, 453, 779-782.

Guyon, I. & Andre, E. (2006). An Introduction to Feature Extraction. In Guyon, I., Gunn, S., Nikravesh, M. and Zadeh, L.A. (Eds.), *Feature Extraction: Foundations and Applications Studies in Fuzziness and Soft Computing*. Springer-Verlag, 1-25.

Hoffmann-Wellenhof, B., Lichtenegger, H. & Collins, J. (2001). Global Positioning System: Theory and Practice. (5th ed.). Wien: Springer.

Hornsby, K. S. & Cole, S. (2007). Modeling Moving Geospatial Objects from an Event-based Perspective. *Transactions in GIS*, 11, 555-573

Jun, J., Guensler, R., and Ogle, J. (2007) Smoothing methods to minimize impact of Global Positioning System random error on travel distance, speed, and acceleration profile estimates, *Transportation Research Record*, 1972, 141–150.

Laube, P. & Purves, R.S. (2006). An Approach to Evaluating Motion Pattern Detection Techniques in Spatio-temporal Data. *Computers, Environment and Urban Systems*, 30, 347-374.

Laube, P., Dennis, T., Forer, P. & Walker, M. (2007). Movement beyond the snapshot - Dynamic Analysis of Geospatial Lifelines. *Computers, Environment and Urban Systems*, 31, 481-501.

Lin, B. & Su, J. (2008). One Way Distance: For Shape Based Similarity Search of Moving Object Trajectories. *GeoInformatica*, 12, 117-142.

Naftel, A. and Khalid, S. (2006). Classifying spatiotemporal object trajectories using unsupervised learning in the coefficient feature space. *Multimedia Systems*, 12, 227-238.

Ozyildiz, E., Krahnstöver. N., Sharma, R. (2002). Adaptive texture and color segmentation for tracking moving objects. *Pattern Recognition*, 35, 2013–2029.

Pfoser, D., & Theodoridis, Y. (2003). Generating semantics-based trajectories of moving objects. *Computers, Environment and Urban Systems*, 27(3), 243–263.

Tsui, S. Y. A. and Shalaby, A., (2006) An enhanced system for link and mode identification for GPS-based personal travel surveys, *Transportation Research Record*, 1972, 38–45.

Salvucci, D.D., & Goldberg, J. H. (2000). Identifying fixations and saccades in eye-tracking protocols. *Proceedings of the Eye Tracking Research and Applications Symposium*, New York: ACM Press, 71-78.

Schüssler, N. and Axhausen, K.W., (2009) Processing GPS raw data without additional information, *paper presented at the 88th Annual Meeting of the Transportation Research Board*, Washington, D.C., January 2009.

Smith, L.I, (2002). *A tutorial on Principal Components Analysis*. Cornell University, USA.

Spaccapietra, S., Parent, C., Damiani, M. L., de Macedo, J. A., Porto, F., and Vangenot, C. (2008). A conceptual view on trajectories. *Data & Knowledge Engineering*, 65 (1), 126-146.

Turchin, P. (1998). *Quantitative Analysis of Movement: Measuring and Modelling Population Redistribution in Animals and Plants*. Sunderland, MA: Sinauer Publishers.

Vlachos, M.; Gunopulos, D. & Kollios, G. (2002). Robust Similarity Measures for Mobile Object Trajectories. *Proceedings 13th International Workshop on Database and Expert Systems Applications*. Washington, DC, USA: IEEE Computer Society, 721- 726.

Zheng, J.-B., Dagan Feng, D., Zhao, R.-C., (2005). Trajectory Matching and Classification of Video Moving Objects. *Proceedings 7th IEEE Workshop on Multimedia Signal Processing*, 2005. 1-4.

Zheng, Y., L. Liu, Wang, L., and Xie, X., (2008) Learning transportation mode from raw GPS data for geographic applications on the web, *paper presented at the 17th World Wide Web Conference*, Bejing, April 2008.