PhD Showcase: Exploring Movement–Similarity Analysis of Moving Objects

PhD Student: Somayeh Dodge
University of Zurich
Winterthurerstrasse 190
8057 Zurich, Switzerland
Phone: +41 44 63 55131
somayeh.dodge@geo.uzh.ch

PhD Supervisor: Robert Weibel
University of Zurich
Winterthurerstrasse 190
8057 Zurich, Switzerland
Phone: +41 44 63 55190
robert.weibel@geo.uzh.ch

PhD Co-Supervisor: Patrick Laube
University of Zurich
Winterthurerstrasse 190
8057 Zurich, Switzerland
Phone: +41 44 63 56634
patrick.laube@geo.uzh.ch

ABSTRACT
Extracting knowledge about the movement of different types of mobile agents (e.g. human, animals, vehicles) and dynamic phenomena (e.g. hurricanes) requires new exploratory data analysis methods for massive movement datasets. Different types of moving objects share similarities but also express differences in terms of their dynamic behavior and the nature of their movement. Extracting such similarities can significantly contribute to the prediction, modeling and simulation dynamic phenomena. Therefore, with the development of a quantitative methodology this research intends to investigate and explore similarities in the dynamics of moving objects by using methods of GIScience in knowledge discovery. This paper presents a summary of the ongoing Ph.D. research project.

Categories and Subject Descriptors
I.5.2 [**Pattern Recognition**]: Design Methodology – *classifier design and evaluation, feature evaluation and selection, pattern analysis, polymorphism, control structures.*

General Terms
Algorithms, Design, Experimentation, Verification.

Keywords
Moving point data mining; moving object; movement parameters; movement behavior; movement pattern; trajectory decomposition; trajectory classification; trajectory similarity.

1. INTRODUCTION
The analysis of moving objects (i.e. entities whose positions or geometric attributes change over time) has recently become the focus of many research projects in the area of geographic information science, with applications in human-computer interaction (HCI), ecology, biology, transportation, social and behavioral sciences. In most cases, since the dimension of the moving object is not as important as its position, moving objects are modeled as moving points (MPOs), whose trajectories (i.e. paths through space and time) can be analyzed. Moving objects in general can be categorized into two major groups of geo-referenced and non-geo-referenced dynamic objects. In other words, some are dynamic objects that move in geographic space and may thus be geographically referenced such as humans, animals, vehicles, or hurricanes while the other group covers entities that move in a non-geographic space, including gaze point movements in eye movement studies or particles in a bubble chamber. All these dynamic objects share similarities but also exhibit differences in terms of their underlying data structure, dynamic behavior and nature of movement. Extracting such similarities can significantly contribute to the prediction, modeling and simulation of the dynamics amongst moving objects. [9, 10]

Research on the development of data mining techniques on knowledge discovery from movement datasets usually strives to conceive generic algorithms. Namely, the developed algorithms should be potentially suitable for different kinds of moving objects from a wide variety of application domains— e.g. animal ecology, fleet management and human behavioral studies. In consequence, it is essential to understand the similarities but also the differences between different types of moving objects and their associated movement parameters and patterns. Trajectory simulation is another area where detailed knowledge of the movement parameters of different moving objects is crucial. Simulating dynamic environmental phenomena, mobility of humans, animals and, or studying human interaction with computers requires extracting knowledge about the dynamic behavior of different types of mobile agents and thus creates challenges in developing new exploratory data analysis methods on massive movement datasets. The better the knowledge about the movement behavior of the particular objects that is simulated, the more realistic the simulation results will be.

The above issues all point to a need for methods for analyzing and classifying the movement behavior of various moving objects, with the aim of determining the similarity of trajectories generated by moving objects. Therefore, this research aims to investigate and explore similarities in dynamic behavior of moving objects. The intention is to develop a conceptual and methodological framework for extracting similarities from trajectories of moving objects by quantitative analysis. In detail, this research addresses the following research questions:

The SIGSPATIAL Special, Volume 1, Number 3, November 2009

a) How similar is the movement of different types of moving objects in space and time?

b) How similar are artificial simulated proxies to the corresponding reference moving objects?

c) How to formalize and define similarity in terms of movement as a general measure appropriate to any kind of moving point object? How to automatically discover spatio-temporal similarities amongst trajectories of moving objects?

d) How to benefit from similarity analysis in order to predict movement of an object under given circumstances? How to determine whether objects of the same type exhibit similar dynamic behavior in a particular situation?

2. MOVING OBJECT DATA MINING

Non-stop generation of space-time trajectories from different kinds of moving entities provides the possibility to discover useful and interesting information about movement of human, animals, vehicles, to find patterns, extract their meaning, and expand our knowledge about the mobile world [26]. A review of the literature on moving object data mining and visualization highlights the importance and significant progress in this area. In this context, [13] gives 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 spatio-temporal data mining techniques, including latest work on data privacy and security issues. Moving object data mining, named mobility data mining [13], as a novel research area is one step of the geographic knowledge discovery process. Mobility data mining aims at analyzing mobility data and extracting useful patterns from trajectory data by the use of efficient algorithms [13, 17]. The following subsections present a brief categorized overview of some of the recent moving object data mining and knowledge discovery approaches. Since the main objective of this research is to discover similarities between dynamic behaviors of different types of mobile agents, more emphasis is placed on similarity studies in section 2.3.

2.1 Trajectory Modeling and Simulation

In general, the path of a moving object, named trajectory, is the subject of interest in moving object data analysis. In order to analyze or simulate typical movement behavior of an object, it is necessary to extract differentiated movement characteristics from monitored trajectories. In this regard, recent years have witnessed a rapid increase of research activities on modeling, simulation and analysis of trajectories. For instance, [2, 3, 5] present different exploratory approaches in order to model and classify trajectories to discover dynamics of different moving object types. Similarly, the simulation of trajectories has been used for diverse purposes, such as ecological modeling [4, 29], spatio-temporal database research [23], and in the evaluation of data mining algorithms [17]. In transportation studies some researchers focused on modeling and extracting knowledge from raw GPS data to detect the mode of transport that people used, with the aim of understanding user behavior [28, 33].

2.2 Movement Pattern Analysis

Movement patterns include any recognizable spatial and temporal regularity or any interesting relationship in movement data. Various data mining tasks, including exploratory data analysis, descriptive and predictive modeling, association rule mining, and other pattern detection techniques have been employed on trajectories in order to extract patterns of movement and discover spatio-temporal behavior of different types of moving objects [11, 17, 18]. Early work on movement pattern analysis includes the simulation study of human adaptive behavior [4] and the methods developed for the spatio-temporal analysis of wild animal movement [16]. Moreover, recent work in this area includes the extraction of movement patterns from trajectories generated by individual users of location-based services [19, 26]; and mining of movement patterns in groups of moving objects [15, 18].

The above publications document significant progress over the past few years. However, a review of the related literature suggests that there is little agreement on the relevant types of movement patterns and only few, isolated definitions of these exist. These studies usually set out with fairly accurate definitions of the patterns they are looking for—as an indispensable prerequisite to data mining [11]—but they tend to be restricted to a selected, narrow set of patterns. Hence, still a fundamental problem and impediment to the development of a comprehensive toolbox of movement analysis techniques can be found: There is neither agreement on the relevant types of movement patterns nor any comprehensive and systematic definition of these [9].

2.3 Trajectory Similarity Analysis

Similarity analysis as an exploratory tool in mobility data mining disciplines has been traditionally applied on time series databases such as financial, marketing and production time series (e.g. stock prices) as well as scientific time series databases (e.g. weather data, sea level data etc.) in order to predict the future trend of data, test hypothesis [1]. Research on finding similarity between trajectories of moving objects initiated from similarity search techniques on time series databases. Current trajectory similarity search techniques, based on their underlying distance measures, can be classified into three categories of spatial, temporal and spatio-temporal similarity.

2.3.1 Spatial similarity

Most previous work focuses on spatial similarity search by looking for similarities of the geometric shape of the trajectories, by ignoring the temporal information. Examples include applying Euclidean distance between trajectories [6, 32], the Edit Distance [7], One-Way Distance [21], Hausdorff distance [14], Fourier descriptors [24], Longest Common Subsequence (LCSS) [31].

2.3.2 Temporal similarity

Temporal similarity of trajectories is performed the same as similarity analysis on time series data sequences, for instance using a P-norm distance or Time Wrapping distance to calculate similarity between two sequences. [7, 25]

2.3.3 Spatio-temporal similarity

Recently, some work has been carried out on spatio-temporal similarity of trajectories. The proposed methods aim at dealing with both spatial and temporal dimensions of trajectories and other dynamic characteristics such as speed and direction. For instance, based on the Euclidean distance [12] proposes a dissimilarity metric between trajectories of different sampling rates to find the K-Most-Similar-Trajectories (K-MST) on R-tree-like structures. On a similar attempt, [30] applied Euclidean distance on trajectories of the same sampling rate to find sub-trajectories with maximum similarity. In this context, [22] introduces different versions of similarity in-between polylines to deal with different similarity search and trajectory clustering tasks. considering speed and direction of the objects over time. To the best of our knowledge, this has been the only work that takes movement primitives into account in similarity search. The distance measure is computed based on the area of a set of polygons formulated between intersection points of trajectories [22]. In another work, Euclidean time-Uniform distance has been introduced in optimal or approximate matching between trajectories under translation and rotation [27]. On a similar attempt an extension of Frèchet distance has been applied to support trajectory similarity join [8].

Concluding the above review of the state of the art, it is obvious that similarity analysis is rather a new topic in the domain of moving object databases and there are still some issues, which are not fully addressed so far. It can be admitted that while proposed similarity search methods for trajectories of moving objects are relatively well developed, most of them are restricted to a specific criterion in order to match the similar trajectories. It is necessary to remark that only few previous approaches have dealt with dynamics of trajectories in similarity search, that is, taking the movement parameters into account in the similarity search algorithm. On the other hand, some regard trajectories as static curves and simply ignore speed and time variables. Therefore, those measures cannot handle different aspects of a spatio-temporal trajectory of moving objects. The proposed measures are very application dependent. Thus, there is a need to develop general and flexible spatio-temporal measures that consider various movement parameters.

3. METHODOLOGY

A four-stage methodology has been developed to achieve the objectives. The methodology consists of the following stages: 1) Conceptual framework of movement; 2) movement features extraction; 3) trajectory similarity search; 4) trajectory similarity search evaluation.

Stages #1 and #2 address the research question (a) and (b), presented in the introduction section, and provide the fundamental framework for the next steps. Stages #3 and #4 address the research question (c) and (d) by developing a generic spatio-temporal similarity search on the trajectories of moving objects. The research is still in progress, currently at stage #3. So far, the fist two stages (i.e. #1 and #2) have been fulfilled.

4. PREVIOUS WORK

4.1 Conceptual Framework of Movement

In order to study the movement behavior of dynamic objects, it is important to take a closer look at movement itself. In other words, it is necessary to know what exactly the parameters are that define movement, what external factors influence movement, and most importantly to understand what types of movement patterns can be composed from these primitives of movement. Hence, the objectives of the first stage of this research are firstly to develop a conceptual framework of the elements defining the movement of different moving objects and secondly the development of a comprehensive classification and definitions of movement patterns. This is indispensable as a basis for the development of pattern recognition and information visualization algorithms that are required to be efficient (i.e. usable on massive data sets), effective (i.e. capable of accurately detecting patterns not artifacts), and as generic as possible (i.e. potentially applicable to different types of movement data).

The conceptual framework describes the rudiments of movement in general. Movement parameters (i.e. speed, acceleration, turning angle, straightness, etc.) are the fundamentals of the proposed framework. On the framework, they are categorized into three groups of primitive (e.g. position, interval), primary derivatives (e.g. distance, duration, speed) and secondary derivatives (e.g. acceleration, spatial distribution, sinuosity). Besides, primitive and derived parameters are organized into spatial, temporal, and spatio-temporal dimensions. Moreover, other principal elements of the conceptual framework are introduced as path types (i.e. continuous and discontinuous), influential and external factors influencing movement, scale and granularity. [9]

The classification of movement patterns is developed based on a review of the pertinent literature, in order to maximize reuse of already existing sufficiently accurate definitions, and minimize redundant, conflicting terminology. Following the conceptual framework, three dimensions of spatial, temporal and spatio-temporal are considered in studying movement patterns. Patterns are categorized into two major groups of generic and behavioral patterns. Generic pattern can be found in any form of behavior that builds on movement regardless of the type of object. In contrast, behavioral patterns, as higher-level patterns, include movement patterns that can solely be found in certain types of moving objects (e.g. certain animal species). In the proposed classification, primitive, as the most basic patterns, and compound patterns are distinguished among the generic movement patterns. A figure summarizing the classification can be bound in [9] and in a wiki1 aiming at community participation on the topic.

The outcomes of this stage are published in [9]. The developed conceptual framework and classification of movement patterns provide the underlying structure for the remainder of this research.

4.2 Movement Features Extraction

The motivation of this stage is to take an analytical look at the movement characteristics and dynamic behavior of different types of dynamic objects and extract possible similarities among movement behaviors of such objects. Therefore, this phase presents a methodology that allows extracting local movement features from the trajectories of different types of moving objects. The methodology consists of three steps, shown graphically in Figure 1: 1) trajectory data preparation; 2) global descriptors computation; and 3) local feature extraction. [10]

4.2.1 Trajectory data preparation

Raw data captured by movement tracking devices usually contain noise, outliers and gaps. Therefore, in order to remove effects of noise and positioning errors of the tracking devices and other

[1] http://movementpatterns.pbwiki.com/Patterns-of-Movement

factors, data cleaning and pre-processing procedures should be applied to achieve more reliable trajectories. The pre-processing phase consists of three steps including filtering, re-sampling, and smoothing.

4.2.2 Global descriptors computation

Movement parameters (i.e. speed, acceleration, turning angle, straightness, etc.), introduced in the conceptual framework, are very different in terms of the values that they can take for each type of moving object. To achieve differentiated results in the characterization of trajectories, the computation of movement parameters should be performed at consecutive scales. Namely, 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.

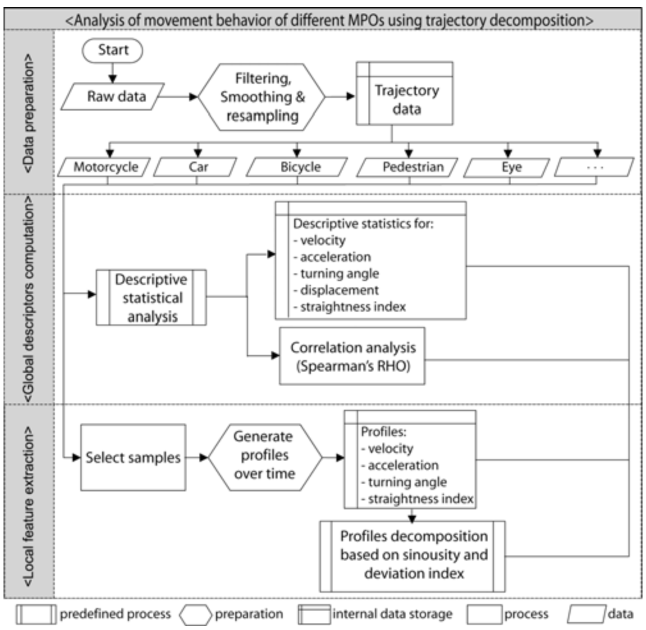

Figure 1. Methodology for extracting the movement behavior of different MPOs [10]

4.2.3 Local feature extraction

In order to reveal more detail in the movement behavior of the moving objects, the proposed approach is to decompose trajectories to a set of meaningful segments of homogeneous movement characteristics. The key element of the methodology is an algorithm that decomposes the different movement parameters profiles based on variations in sinuosity and deviation from the median line, hence enabling the extraction of local movement features from trajectories of moving objects. 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. Figure 2 illustrates the essentials of the profile decomposition algorithm. [10]

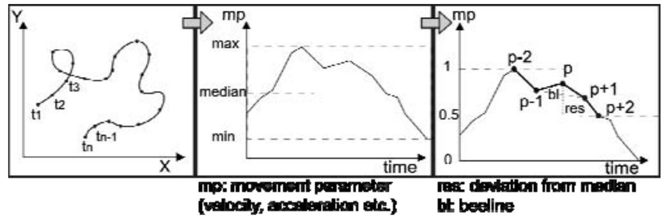

Figure 2. Basic elements of movement parameter profiles [10]

The developed 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). The proposed methodology can inform developers of pattern recognition and data mining algorithms about similar and dissimilar types of moving objects, hence allowing the design of rigorous algorithm evaluation strategies. 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. It can also be used to classify unknown moving objects into previously identified 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). [10].

This work has been published in [10]. The feasibility of the developed methodology has been examined through a set of empirical experiment. The proposed methodology has been applied to classify trajectories of unknown moving objects by similarity to the trajectories of previously learned moving objects. The conducted experiments not only demonstrated the feasibility of the proposed methodology but also provided interesting empirical results. The experiments provided evidence about the similarities and differences that exist among different types of moving objects in the transportation domain. The results showed that the methodology can successfully detect the mode of transport from unknown trajectories of people using different transportation means. [10]

5. ROAD AHEAD

5.1 Trajectory Similarity Search

The main focus of this stage is the development of a spatio-temporal similarity search method for the effective detection of moving objects trajectories with similar dynamic patterns. Here, similarity search tasks are classified in two modes of concurrence and coincidence movement patterns. The aim of the concurrence analysis is to investigate the similarity of movement parameters (e.g. speed, acceleration, direction) derived from trajectories of moving objects over time in a multidimensional feature space. On the other hand, the coincidence analysis studies similarity of moving objects in space and time. The similarity is computed by aligning two trajectories. Alignments can be global (on entire trajectories) or local (on subsequences of a trajectory). In order to find segments of profiles with similar dynamic behavior, the trajectory decomposition algorithm, proposed in section 3.2, together with the favored similarity measure will be applied. The work is still in progress. The following strategy is considered in this methodology.

5.1.1 Generating and decomposing movement parameters profiles

As the first step, the movement parameter profiles need to be computed from trajectories of objects. Figure 3a illustrates sample movement parameter profiles as building blocks of the multidimensional feature space. Among the movement parameters taken from the conceptual framework, velocity and direction (i.e. azimuth or turning angle) have been considered as essential variables for similarity search. The reason is that these movement descriptors allow defining relative movement.

5.1.2 Generating a multidimensional feature space

The outcomes of the first step are then employed to generate a multidimensional (i.e. 3D) feature space of the decomposed profiles of velocity and azimuth (or turning angle) over time. Each of the movement parameters will constitute one dimension of the multidimensional feature space for trajectories (Figure 3). This provides a multidimensional time series for each trajectory.

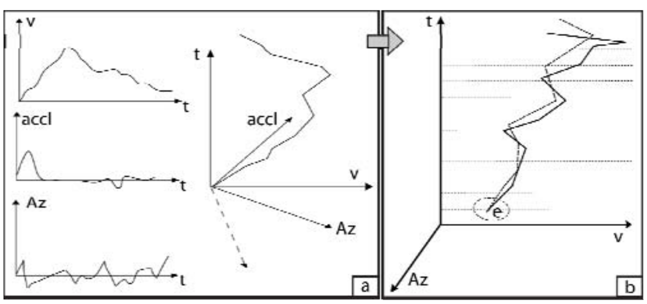

Figure 3. Similarity search on the multidimensional feature space composed of movement parameter profiles

5.1.3 Similarity search

The similarity measure is defined in a multidimensional feature space. In order to compute the similarity of the multidimensional time series derived from the subject trajectories two strategies are currently evaluated:

Strategy #1: in the 3D feature space composed of velocity, azimuth, and time (Figure 3b) the average Euclidean distance between the two 3D profiles derived from corresponding trajectories will be computed as similarity measure. If the computed distance exceeds a specified threshold (i.e. e) two trajectories are considered to be dissimilar.

Strategy #2: First, the trajectory segmentation algorithm, described in section 4.2.3, is applied on the movement parameter profiles. This yields a set of homogeneous profile segments that can facilitate similarity search. Subsequently, similarity measures related to the concepts of Edit distance and Levenshtein distance [20] will be employed to calculate the similarity between sequences of trajectory segments.

5.2 Trajectory Similarity Search Evaluation

Following the implementation of the basic similarity search platform, a set of experiments will be carried out in a controlled evaluation mode. Different kinds of movement data such as GPS tracks of human or vehicles, animal tracking data, radar data sets of hurricane trajectories will be used. The aim of this step is to test the validity of the implementation and to evaluate the efficiency and usability of the developed similarity measure.

6. CONCLUSION AND OPEN QUESTIONS

The paper introduces an ongoing Ph.D. research that aims to explore the similarities, not only among moving objects of the same type but also between different moving objects of different species. A quantitative methodology is developed to investigate similarities between both movement characteristics of different objects and their patterns of movement. The outcome of this research can contribute to variety of applications such as ecology and biogeography studies, by modeling or simulation of the migration of animals or birds; to transportation studies, by automatic transportation mode detection Moreover, it can potentially support the prediction of possible hurricane tracks in hazard management, by extracting similarities between hurricanes occurred in past.

While the research is still proceeding, a conceptual framework of movement, as well as a methodology of trajectory decomposition and classification have been developed. As upcoming results, a spatio-temporal similarity measure for trajectories of moving objects will be developed. And finally, the feasibility of the methodology will be evaluated in different disciplines such as environmental hazard management, modeling or simulation of the migration of animals or birds; transportation studies.

With reference to the objectives of this research, that is to address the problem of trajectory similarity search in a broad domain, some open questions can be raised as follows:

1) Is similarity a general measure or is it application-specific?
2) Should similarity be considered as a specific movement pattern?
3) How can similarity measures be verified? Since usually the end product of the similarity search techniques are rather subjective.
4) How to address similarity of trajectories regarding their underling context?

7. ACKNOWLEDGMENTS

This research is funded by the University of Zurich.

8. REFERENCES

[1] Agrawal, R., Faloutsos, C., and Swami, A. N. 1993. Efficient Similarity Search In Sequence Databases. In Proceedings of the 4th international Conference on Foundations of Data Organization and Algorithms. D. B. Lomet, Ed. Lecture Notes In Computer Science, Springer-Verlag, London, 730, 69-84.

[2] 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.

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

[4] Blythe, P.W., Miller, G.F. and 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.

[5] 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.

[6] Cai, Y., and Ng., R. 2004. Indexing spatio-temporal trajectoires with Chebyshev polynomials, Proceedings of the 2004 ACM SIGMOD international conference on Management of data, 599 - 610.

[7] 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.

[8] Ding, H., Trajcevski, G., and Scheuermann P. 2008. Efficient maintenance of continuous queries for trajectories. GeoInformatica, 12, 3, 255-288.

[9] Dodge, S., Weibel, R. and Lautenschütz, A.-K. 2008. Towards a Taxonomy of Movement Patterns. Journal of Information Visualization, 7, 240-252. DOI= http://dx.doi.org/10.1057/palgrave.ivs.9500182.

[10] Dodge, S., Weibel, R., Forootan, E. Revealing the Physics of Movement: Comparing the Similarity of Movement Characteristics of Different Types of Moving Objects, Journal of Computers, Environment and Urban Systems, 2009, in press. doi:10.1016/j.compenvurbsys.2009.07.008

[11] Fayyad, U., Piatetsky-Shapiro, G. and Smyth, P. 1996. From Data Mining to Knowledge Discovery in Databases. AI Magazine, 17, 3, 37-54.

[12] Frentzos, E., Gratsias, K., and Theodoridis, Y. 2007. Index-based Most Similar Trajectory Search. Proceedings of the 23rd IEEE International Conference on Data Engineering (ICDE’07), 816-825.

[13] Giannotti, F. and Pedreschi, D. 2007. (eds.) Mobility, Data Mining and Privacy – Geographic Knowledge Discovery. Springer.

[14] Goodrich, M.T., Mitchell, J.S.B., & Orletsky, M.W. 1999. Approximate geometric pattern matching under rigid motions. IEEE Transaction on Pattern Analysis and Machine Intelligence, 21, 4, 371-379.

[15] Gudmundsson, J., van Kreveld, M.J. and Speckmann, B. 2004. Efficient Detection of Motion Patterns in Spatio-temporal Data Sets. *ACM GIS 2004*, 250 -257.

[16] Imfeld, S. 2000. Time, Points and Space – Towards a Better Analysis of Wildlife Data. PhD Thesis, Department of Geography, University of Zurich.

[17] Laube, P. and Purves, R.S. 2006. An Approach to Evaluating Motion Pattern Detection Techniques in Spatio-temporal Data. Journal of Computers, Environment and Urban Systems, 30, 347-374.

[18] Laube, P. Analysing Point Motion – Spatio-Temporal Data Mining of Geospatial Lifelines. 2005. PhD Thesis, Dept. of Geography, Univ. of Zurich.

[19] Lee, J.W., Paek, O.H. and Ryu, K.H. 2004. Temporal Moving Pattern Mining for Location-based Services. Journal of Systems and Software, 73: 481- 490

[20] Levenshtein, V. 1966. Binary Codes Capabale of Correcting Deletions, Insertions, and reversals. In: Cybernetics and Control Theory, 10, 8, 707-710.

[21] Lin, B. and Su, J. 2008. One Way Distance: For Shape Based Similarity Search of Moving Object Trajectories. GeoInformatica, 12, 117-142.

[22] Pelekis, N.; Kopanakis, I.; Marketos, G.; Ntoutsi, I.; Andrienko, G. and Theodoridis, Y. 2007. Similarity Search in Trajectory Databases. In proceedings 14th International Symposium on Temporal Representation and Reasoning, 129-140.

[23] Pfoser, D., and Theodoridis, Y. 2003. Generating semantics-based trajectories of moving objects. Computers, Environment and Urban Systems, 27, 3, 243-263.

[24] Rafiei, D. and Mendelzon, A. 2002. Efficient retrieval of similar shapes. The VLDB, The International Journal on Very Large Data Bases, 11, 17-27. DOI= http://dx.doi.org/10.1007/s007780100059.

[25] Sakurai, Y., Yoshikawa, M., and Faloutsos, C. 2005. FTW: Fast similarity search under the time warping distance, In Proceedings of ACM Symposium on Principles of Database Systems, 326-337.

[26] Smyth, C.S. 2001. Mining mobile trajectories. In: Miller, H.J. & Han, J. (eds.): Geographic Data Mining and Knowledge Discovery, Taylor & Francis, 337-361.

[27] Trajcevski, G., Ding, H., Scheuermann, P., Tamassia, R., and Vaccaro, D. 2007. Dynamics-aware similarity of moving objects trajectories. In Proceedings of the 15th Annual ACM international Symposium on Advances in Geographic information Systems, (Seattle, Washington, November 07 - 09, 2007). GIS '07. ACM, New York, NY, 1-8.

[28] 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.

[29] Turchin, P. 1998. Quantitative Analysis of Movement: Measuring and Modelling Population Redistribution in Animals and Plants. Sunderland, MA: Sinauer Publishers.

[30] van Kreveld, M. and Luo, J. 2007. The definition and computation of trajectory and subtrajectory similarity. In Proceedings of the 15th Annual ACM international Symposium on Advances in Geographic information Systems (Seattle, Washington, November 07 - 09, 2007). GIS '07. ACM, New York, NY, 1- 4.

[31] Vlachos, M., Kollios, G. & Gunopulos, D. 2002. Discovering similar multidimensional trajectories, ICDE '02: Proceedings of the 18th International Conference on Data Engineering, IEEE Computer Society, 673–684

[32] Yanagisawa, Y., Akahani, J., and Satoh, T. 2003. Shape-Based Similarity Query for Trajectory of Mobile Objects. In Proceedings of the 4th international Conference on Mobile Data Management. M. Chen, P. K. Chrysanthis, M. Sloman, and A. B. Zaslavsky, Eds. Lecture Notes In Computer Science, Springer-Verlag, London, 2574. 63-77.

[33] 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).