Analysing Behaviour of Moving Objects

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***Abstract*- The advances of GPS technology and wide-ranging usage of wireless communication devices have facilitated the collection of large amount of spatiotemporal data. Of special interest are data related to moving objects. By modelling and analyzing moving objects data, we learn about the moving objects behaviour and even predict their future locations. Discovery of patterns and prediction of future movement can greatly influence different fields. Devising the correct inference is a scientific and computational challenge. Fundamentals of moving objects' representation and space partitioning are presented. Markov models are described in general along with their application to spatiotemporal prediction. Process of prediction and possible enhancements are shown. Comparison of related work and some disadvantages are given.**

***Keywords*- moving object, spatiotemporal data, pattern recognition, spatiotemporal data mining, prediction, Markov chains**

I. INTRODUCTION

All moving things in the real world can comprise spatiotemporal data, containing time and space attributes simultaneously [2]. Data that are moving in time with changes of their location or shape describe a moving object.

In many applications, knowing moving objects location in advance is very appreciable. Discovery of patterns and prediction of future movement can greatly influence different fields. Some of examples are analysing wild animals' movement in order to predict their migrations, monitoring vehicles and analyzing their movement in order to predict traffic congestions, predicting the movement of a mobile user roaming around and changing access points to assure given level of quality of service in wireless networks or analysing and predicting the movement of aircraft in combat in order to develop defending strategies.

There are also situations in which determining the exact position of a moving object is not possible, for example when the moving object enters a shadow area of GPS, and estimating the location by referencing the previous ones which were provided in visible regions, becomes necessary.

As technology advances, we encounter more available data on moving objects, thus increasing our ability to mine spatiotemporal data [3]. We can use these data to analyze moving objects behaviour and to predict their future locations.

In [16], authors find out that human movement shows a high degree of temporal and spatial regularity. Froehlich and Krumm [8] show that a large portion of a typical driver's trips are repeated. It is thus reasonable to expect to extract that regularity, describe it and use it to predict future movement.

II. MOVING OBJECTS

A. Representing moving objects

Although the movement is continuous, GPS and communication technologies allow us to sample an object's position, i.e. to obtain the position at discrete instances of time [1]. Interpolating these samples, we can extract object's movement. The simplest approach is to use linear interpolation. The sampled positions become the end points of line segments of polylines, and the movement of an object is represented by entire polyline in three-dimensional space. The movement of an object (i.e. the trace of an object) is called trajectory (see Figure 1).

Trajectories can have different characteristics depending on the characteristics of moving objects they represent, or depending on the application requirements. Two most important general characteristics of trajectories are direction and speed of the movement.

Trajectories relate to pertaining spatial environment (such as ground cover, nature objects or objects in urban environment) or to other trajectories (moving objects of the same class or other moving objects). Further, trajectories can enter or can cross a spatial environment, or trajectories can (not) be within a spatial environment; they intersect, meet and can be near or far to other trajectories.

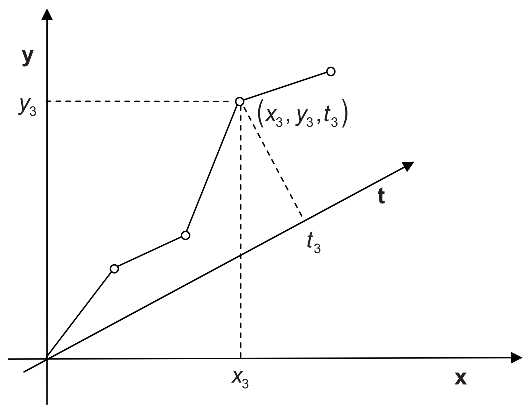

Figure 1 Trajectory - x and y represent coordinates and t represents time

For example, wild animal is passing through the wood near the highway, crossing the river and meeting its prey's path.

B. Space partitioning

Space partitioning is the process of dividing a space into disjoint subsets. Points in space can then be identified to lie in exactly one of the subsets. Partitioning is not only an easier way to represent continuous space in computer, but also a semantically reasonable approach – two points on the map might have very close but different coordinates, having the same meaning.

The simplest way is to divide space into predefined uniformly sized cells. Depending on application field, it could be meaningful to divide space into irregular subsets where each subset encompasses semantically similar part of space. The examples of space partition are shown in Figure 2 and Figure 3.

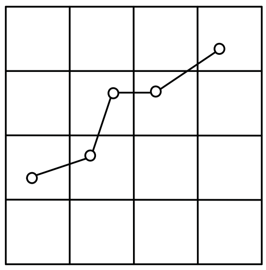

Figure 2 Space partition into uniformly sized cells

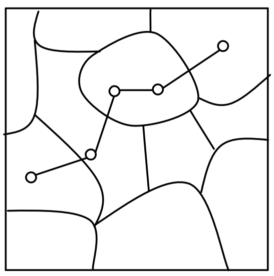

Figure 3 Space partition into non-uniform subsets, possibly representing semantically similar parts of space

In [12] the authors indicate two critical shortcomings of the space-partitioning approach: inability to solve the answerless problem and high dependence of space division size.

- inability to solve the answerless problem

If, for example, we define a dense region as a cell having more than two points within it, intuitively dense region will not be recognized as dense because points are spread over three different cells (see Figure 4).

- high dependence of space division size

The precision of pattern discovery depends on how big a cell size is. Dividing space into large number of smaller cells leads to better accuracy, but also to higher computational complexity. Potential size of cell depends also on how far an object moves in space and how long is the time period of movement.

In order to overcome these problems, in [12] the authors suggest to reveal regions (independent of space partition) that an object frequently visits by applying data mining techniques.

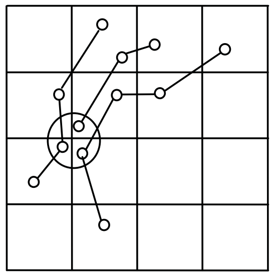

Figure 4 Disadvantage of space partitioning – Dense region (three points in the circle) is not recognized as dense because points are spread over three different cells

III. Analyzing Moving Objects' Behaviour and Predicting their Future Location

First step in predicting the movement of moving objects is learning from data about their previous (historical) locations in order to extract regularities in movement patterns. This process is called spatiotemporal data mining. Although data mining research has been expanding in a variety of fields in recent years, data mining technology for moving objects databases is still in an emerging stage of development. Since data managed in a moving object database is highly dynamic and has spatiotemporal semantics (e.g. underlying cell topology), new data mining technologies should be developed [21].

Several prediction techniques are used to model moving object's future location prediction problem: neural networks ([17][18]), Markov models ([13][21]), specific types of dynamic Bayesian networks like hidden Markov models or Kalman filter ([11][7][8]).

A. Markov Models

Consider a system which may be described at any time as being in one of set of N distinct states $S_0,..,S_{n-1}$. At regularly spaced discrete times, the system undergoes a change of state (possibly back to the same state) according to set of probabilities associated with the state. We denote the time instants associated with the state changes at $t = 0,1,\ldots$, and we denote the actual state at time t as s_t [19]. X is a set of stochastic variables $\{X_t, t \in T\}$.

A stochastic process which fulfils the Markov property [22]:

$$
\begin{aligned}
&P(X_{t+1} = s_{t+1} \mid X_t = s_t) \\
&= P(X_{t+1} = s_{t+1} \mid X_t = s_t, X_{t-1} = s_{t-1},..,X_0 = s_0)
\end{aligned}
$$

is called a first order Markov chain. The Markov property states that the probability of getting into an arbitrary state at time $t+1$ only depends upon the current state at time t, but not on the previous states.

A stochastic process which fulfils:

$$
\begin{aligned}
&P(X_{t+1} = s_{t+1} \mid X_t = s_t,.., X_{t-n+1} = s_{t-n+1}) \\
&= P(X_{t+1} = s_{t+1} \mid X_t = s_t, X_{t-1} = s_{t-1},..,X_0 = s_0)
\end{aligned}
$$

is called a n-th order Markov chain. In this process the probability of getting into the next state depends upon the n previous states. Commonly the term Markov chain is used as a synonym for a first order Markov chain.

For the following consideration it is assumed that the chains are time-homogeneous:

$$a_{ij} := P(X_{t+1} = i \mid X_t = j) = P(X_t = i \mid X_{t-1} = j),$$
$$\forall t \in T, \forall i, j \in S.$$

This means that transition probabilities between states are constant in time. Vice versa in nontime-homogeneous Markov chains p_{ij} may vary over time. Time-homogeneous chains are often called homogeneous Markov chains.

For a homogeneous Markov chain the transition probabilities can then be noted in a time independent stochastical matrix A:

$$A = [a_{ij}], a_{ij} \geq 0 \forall i, j \in S, \sum_{j \in S} a_{ij} = 1.$$

A is called the transition matrix. Along with the initial distribution vector:

$$\pi = [\pi_i], i \in S, \pi_i = P(X_0 = i)$$

it follows that the common distribution of the stochastic variables is well-defined, and can be computed as:

$$P(X_0 = s_0, .., X_t = s_t) = \pi_{s_0} a_{s_0 s_1} .. a_{s_{t-1} s_t}.$$

It can be shown that the probability of getting in m steps to state j, starting from state i:

$$a_{ij}{}^m := P(X_{t+m} = j \mid X_t = i)$$

can be computed as the m-th power of the transition matrix:

$$a_{ij}{}^m = A^m[i, j].$$

Recapitulating, a first-order time-homogeneous Markov Chain can be defined as a 3-tuple, consisting of the set of states S, the transition matrix A and the initial distribution vector π:

$$\theta = (S, A, \pi).$$

The example of Markov chain with three states is given in Figure 5.

Hidden Markov models in addition have observation symbols and probability of their emission in each state.

B. *Markov Models for Spatiotemporal Data*

It is naturally imposed to model spatiotemporal problem in a way presented in Figure 6. Cells (partition subsets) are states of Markov model. Transitions, i.e. probabilities of transitions between states are predefined or calculated from previous data. There are other possibilities to choose structure and parameters of Markov model. In [13] the author converts GPS data into sequences of road segments (states of Markov model), in order to make predictions about vehicle's future path, elevation and turns. His map matching algorithm matches GPS points to road segments, taking into account nearby roads and constraints such as speed limit of the road. Further, he evaluates Markov models of various orders.

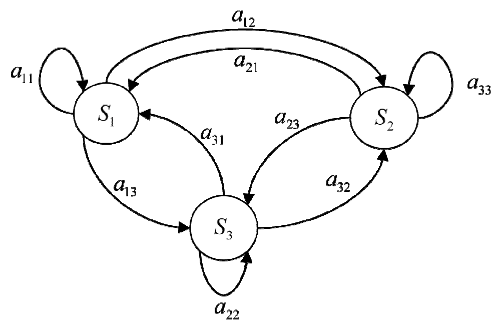

Figure 5 Example of Markov chain with three states

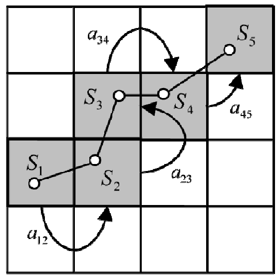

Figure 6 Markov model for spatiotemporal data

It gets more complicated to predict the movement of a moving object that does not move along the road, i.e. when movement does not depend on the roads topology.

In [12] authors map states to regions discovered by clustering algorithms.

C. *Similar problems*

Above observations assume that exact location of moving object is known (e.g. collected from GPS) and that it is, for its purpose, precise enough. It should be mentioned that predicting moving objects' future locations encompass also problems dealing with imprecise information.

One problem is prediction without having GPS. For example, mobile user is roaming and changing access points. According to signal strength and prior visited access points we would like to guess user's exact location.

The other problem arises because of imprecise GPS devices. For example, the car is moving along the road network, but GPS device located in the car would not give coordinates that match coordinates of the road. According to road network and prior driver's locations, we would like to guess which road segment the driver is driving on.

These problems are often modelled by hidden Markov models.

D. *Modelling Process and Prediction*

The process of creating the model, learning and finally predicting the movement, from author's point of view, is given in Figure 7.

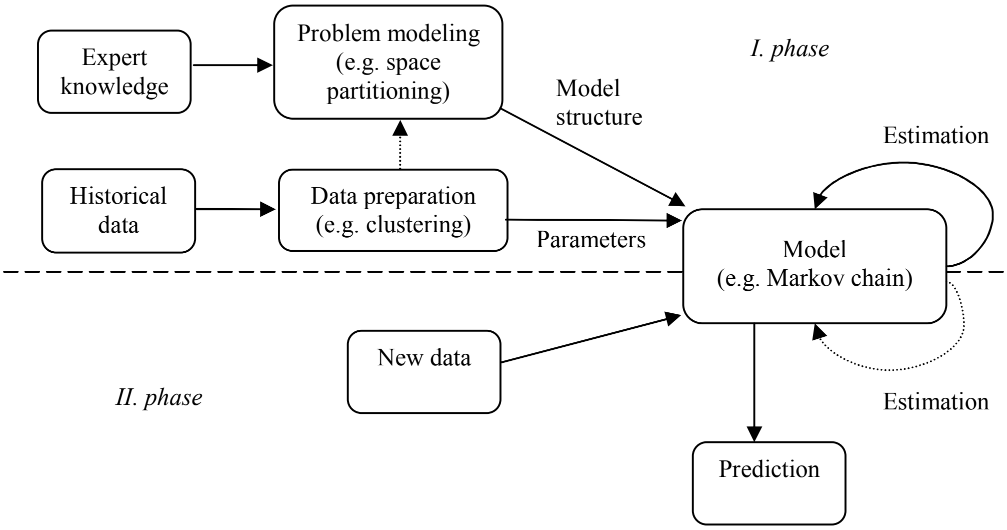

Figure 7 Modelling process and prediction

In the first phase, with a help from an expert in application area, the problem is modelled (for example space partition, model states and transitions are defined). Further on, the gathered historical data are prepared (using for example clustering techniques). They are eventually used to define model structure (for example, choice of states) and then iteratively used to estimate the model parameters. In the second phase, given new data using prepared model and appropriate algorithms, the prediction is done. New data can be used to estimate model parameters, too. Presence of particular process elements differ for different application fields. For example, expert knowledge could be included just to formulate problem or it could be used in an iterative process of parameters estimation.

Automation of this process, which means for example embedding expert knowledge without model perturbation and independence of application area, could be great improvement of former work.

IV. RELATED WORK

Considerable research has been done in various application areas so far.

G. Yavas et al. [6] consider mobility prediction a hot topic in management research field. J.M. François et al. [7] claim that prediction can be particularly useful to assure given level of quality of service despite the typically large jitter and error rates in wireless networks.

J.Froehlich and J.Krumm [8] predict the route of a vehicle. They claim prediction is the missing piece in several proposed ideas for intelligent vehicles. Prediction is useful for giving the driver warnings about upcoming traffic hazards or information about upcoming points of interest, including advertising. In their work, C.S. Jensen et al. [9] track a population of vehicles. They list a range of applications that may utilize this kind of tracking, such as mobile services in relation to traffic monitoring, collective transport, and the management of fleets, e.g., of emergency vehicles, police cars, delivery trucks, and vehicles carrying dangerous or valuable cargo.

In his work, J. Petzold [14] presents context prediction evaluated by the people walking through the office building, recording their movements on PDA.

In [20] authors present methods for person motion prediction in order to enables a mobile robot to keep track of persons in its environment and to improve their behaviour. They state that robots operating in populated environments can improve their service if they react appropriately to the activities of the people in their surrounding and not interfere with them.

D.W.Sims et al. [10] analyse large amount of data representing displacements of diverse marine predators – sharks, bony fishes, sea turtles and penguins, while A. Franke et al. [5] encapsulate movement and kill-site behaviour in three wolf packs.

Furthermore, J. Krumm and E. Horvitz [4] mention usefulness of next location prediction in ubiquitous computing research. As they claim, beyond current object location, location-based services can be developed about object future location, providing more efficient service.

Some work has been done concerning moving objects in general [3] [15].

It is worth to mention a recent database research on moving objects [1][2], where important issues are development of spatiotemporal databases to support moving objects, efficient indexing techniques and efficient extraction of spatiotemporal data.

In Table 1, comparison of some above mentioned works is given. Some of advantages and disadvantages, from the author's point the view, are induced.

Table 1 Comparison of related research

Reference	Moving objects	Method	Technology[1]	Application area	Advantages	Disadvantages
[7]	Mobile users (walking or driving)	Hidden Markov model (HMM)	GPS or antenna	Predicting the next router that host will be linked to in order to assure high level of service quality	Non-similar patterns distinction; Model states are not predefined (they depend on the data)	Number of models grows as the number of neighbour access points squared; Impossibility to predict future locations in new areas
[8]	Vehicles	Clustering, measuring distance	GPS	Predicting end-to-end route of a vehicle	Predicting driver's entire route not only destination; Independence of map matching	Assuming to have given driver's historical data; Impossibility to predict future locations in new areas
[9]	Vehicles	Tracking techniques (point-, vector- and segment-based)	GPS (INFATI data [23])	Tracking population of vehicles and predicting their movement	The tracking component can be used in a variety of applications; Combining different prediction techniques into a single robust tracking technique	Very naive and simple prediction algorithm
[13]	Vehicles	Markov model	GPS	Predicting a driver's near-term future path for giving the driver warnings about upcoming road situations	Simple and accurate algorithm; Prediction is based on only a single previous observation of a few road segments	Short-term route predictions; Impossibility to predict future locations in new areas
[14]	Persons	Artificial Neural Networks	Manually location recording on PDA	Predicting the indoor movement, i.e. the next room user will enter in office building	Comparison of several prediction techniques; Predicting not only future location, but the duration of stay at and the time when person is probably changing to a new location	Manually location recording; Impossibility to predict future locations in new areas; Applicability solely on indoor places or other places with the clear space division
[3]	Generally	Clustering, measuring distance	GPS (INFATI data)	Any, but tested on data about vehicles' movement	Using clusters instead of raw data (which is cheaper to mine); Exceptional points removal	Assuming periodic movement (the same for each object's data); Impossibility to predict future locations in new areas
[20]	Persons	HMM, Clustering	Laser-range finders	Improving robot's behaviour in populated environments by keeping track of persons and predicting their movement	Long-term prediction; Maintaining and estimating positions of multiple persons; Complete solution (from data collection to prediction)	Clustering depends on trajectories length; Impossibility to predict future locations in new areas
[5]	Animals	HMM	GPS (collars and manually recording from aircraft)	Predicting of wolf kill-sites for gaining insight into predator-prey dynamics	Examining interaction between predator and prey; Exact location independence (measuring distance, angle and travel rate instead of solely coordinates)	Predicting only kill-sites, not future locations; Manually preys' location recording

[1] used to get testing data

V. PROBLEMS

Disadvantage of related work is in most cases considering only location and time as attributes of moving object's movement. We believe that adapting model with embedding knowledge about geospatial conditions (e.g. type of a habitat, climate, and various objects' vicinity) that pertain to the location and temporal conditions (e.g. season, time of the day) leads to a more accurate model about moving objects behaviour. The most of additional attributes can be extracted from coordinates and time attributes. Knowing space coordinates, attributes such as vegetation, altitude or type of road can be scanned from geospatial maps. Similarly, knowing time attribute, attributes such as season, temperature or rainfall can be get from historical data collected in weather station.

Furthermore, the model (in the way it is handled in previous work) assumes disposing of an amount of training data concerning observed area, i.e. area in which prediction have to be made. It means that we are not able to predict the object's movement in areas where this object has never been before. We believe that it is possible to adapt existing model in order to predict movement in the new areas. Problem could be modelled considering the analogous areas as the same, thus allowing the data collected at one area to be used as training data for other areas, too.

Another possible improvement could be in supplementing model with expert knowledge about certain moving object characteristics and behaviour. It could be very useful to find the automatic way to embed expert knowledge into the model, in order to enhance the prediction accuracy. That would facilitate build of model independent on any problem field deal with moving objects.

VI. CONCLUSION

Knowing moving objects' behaviour and predicting moving objects' future locations is in many applications very useful. Advances in GPS and wireless technologies have enabled collecting large amount of spatiotemporal data. Beside analysis which we could perform to extract some regularity in the movements and get better insight into moving objects' behaviour, the great issue is to predict moving object's next movement. There are situations in which we want to know moving object's position in advance or in which determining the exact position of a moving object is not possible. It could be also possible to predict potential movement of the whole class of moving objects or even interaction of different classes of objects, by analyzing previous data and their interdependence.

Some common methods are used to derive inferences about moving objects, but there is a lot of space for research and improvements. The main idea is to make inference according to prior locations, but also to include knowledge about type of a habitat that pertains to the location and knowledge about moving objects' behaviour.

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