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Automation of the Moving Objects Movement Prediction Process Independent of the Application Area

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Abstract. Whereas research on moving objects is involved in a variety of different application areas, models and methods for movement prediction are often tailored to the specific type of moving objects. However, in most cases, prediction models are taking only historical location in consideration, while characteristics specific to certain type of moving objects are ignored. In this paper, we presented a conceptual model for movement prediction independent on an application area and data model of moving objects considering various object's characteristics. Related work is critically evaluated, addressing advantages, possible problems and places for improvement. Generic model is proposed, based on an idea to encompass missing pieces in related work and to make the model as general as possible. Prediction process is illustrated on three case studies: prediction of the future location of vehicles, people and wild animals, in order to show their differences and to show how the process can be applied to all of them.

Keywords. moving object, spatiotemporal data, movement prediction, generic model for movement prediction

1. Introduction

Recent wide-ranging usage of Global Positioning System (GPS) devices and wireless communication devices, together with enhancements of supportive technology, induced the expansion of the research on moving objects. By modelling and analyzing moving objects data, we learn about the moving objects behaviour and even become able to predict their future locations [16].

All moving objects in the real world comprise time and space attributes simultaneously, with characteristic of having changeable location or shape through the time [23]. In many applications, knowing moving objects locations in advance can be substantial. Discovery of behavioural patterns and prediction of future movement can greatly influence different fields. Examples are the analysis of the wild animals' movement in order to predict their migrations and predator-prey behaviour [7] [24], monitoring and analysis of vehicle movement in order to predict driver's intentions [15] or traffic congestions [13], mobile user movement and access point availability prediction in order to assure the requested level of quality of service in wireless networks [6]. There are also situations in which the exact position of a moving object cannot be determined, for example when the moving object enters a shadow area of GPS and the estimation of future location by tracking the previous ones that were provided in visible regions becomes necessary [24].

As technology advances, more available data about moving objects is encountered, thus increasing ability to mine spatiotemporal data [5]. In [9], researchers found 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 routes are repeated. It is thus reasonable to expect the extraction of the regularity, its description and usage in prediction of future movement.

Different data mining techniques can be used to extract behavioural patterns from moving objects data [5] [11], several prediction techniques can be used to model and predict moving object's future location, such as neural networks, Markov models, and specific types of dynamic Bayesian networks like hidden Markov models or Kalman filter [3] [6] [7] [14] [20]. Still, all aforementioned methods have to be adapted to deal with moving object's data. Furthermore, the most of them focus on managing historical and current movement data of moving objects and only a few of them have been proposed to deal with moving object's future movement prediction [21].

Paper is organized as follows: In the next chapter related work is critically evaluated, addressing advantages, possible problems and limitations. In chapter 3 according to problems addressed in chapter 2, objectives and places for improvement are suggested. Schema of prediction process is presented, based on an idea to encompass missing pieces in related work and to make the prediction model as general as possible. Conceptual data model independent of application area and moving object type is proposed. In chapter 4 three case studies illustrates prediction process, in order to show differences between different moving object types and to show how the process can be applied to all of them. Conclusion is made in chapter 5 with an announcement of the future work.

2. Related Work

Considerable research on moving objects has been done in various application areas so far. 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 warnings about upcoming traffic hazards or giving information about upcoming points of interest, including advertising, to the driver. C.S. Jensen et al. [13] 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 [9] authors present methods for person motion prediction in order to enable a mobile robot to keep track of people in its environment and to improve its 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 in the same time not interfering with them.

J. Petzold [20] presents context prediction evaluated by the people walking through the office building, recording their movements on PDA.

G. Yavas et al. [27] consider mobility prediction a hot topic in management research field. J.M. François et al. [6] claim that prediction can be particularly useful to assure the given level of quality of service despite the typically large jitter and error rates in wireless networks.

D.W.Sims et al. [25] analyse large amount of data representing displacements of diverse marine predators – sharks, bony fishes, sea turtles and penguins, while A. Franke et al. [7] encapsulate movement and kill-site behaviour in three wolf packs.

Furthermore, J. Krumm and E. Horvitz [15] mention usefulness of next location prediction in ubiquitous computing research. As they claim, beyond current object location, location-based services can be developed by taking into account object future locations, providing more efficient service.

Some work has been done concerning moving objects in general [5][26]. It is also worth to mention a recent database research on moving objects [4][23], where important issues are development of spatiotemporal databases to support moving objects, efficient indexing techniques and efficient extraction of spatiotemporal data.

Shortcoming of related work is in most cases considering only location and time as attributes of moving object's movement (Recently, some ideas of enriching object's movement data with geographical and semantic information is proposed [10][1][2]). Furthermore, the prediction (in the way it is handled in previous work) assumes dispose of an amount of training data concerning observed area, i.e. area in which prediction has to be made. It means that we are not able to predict the object movement in areas where the object has never been before. In Table 1 and Table 2 comparison of some aforementioned works is given.

3. Automation of the Modelling Process and Prediction

Based on an idea to encompass missing pieces in related work and to make the movement modelling and prediction process as general as possible, we will present generic model and propose the conceptual data model independent of application area and independent of moving object type.

Table 1. Comparison of related work (1/2)

Moving objects	Application area	Method	Technology	Advantages	Limitations
Mobile users (walking or driving)	Predicting the next router that a host will be linked to in order to assure high quality of service level [0]	Hidden Markov model (HMM)	GPS or antenna	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; Impossible to predict future locations in new areas
Vehicles	Predicting end-to-end route of a vehicle [0]	Clustering, similarity measuring	GPS	Predicting driver's entire route, not only destination; Independence of map matching	Assuming to have been given driver's historical data; Impossibility to predict future locations in new areas
Vehicles	Tracking populations of vehicles and predicting their movement [0]	Tracking techniques (point-, vector- and segment-based)	GPS (INFATI[1] data)	The tracking component can be used in a variety of applications; Combining different prediction techniques into a single robust tracking technique	Very simple short-term prediction algorithm
Vehicles	Predicting a driver's near-term future path for giving the warnings about upcoming road situations [0]	Markov model	GPS	Simple and accurate algorithm; Prediction is based on only a single previous observation of a few road segments	Short-term route predictions; Impossible to predict future locations in new areas

[1] INFATI is a Danish acronym for "INtelligent FArtTIlpasning" (Intelligent Speed Adaptation). INFATI data is data about drivers' locations collected during the INFATI project. More details in [12].

Table 2. Comparison of related work (2/2)

Moving objects	Application area	Method	Technology	Advantages	Limitations
People	Predicting the indoor movement, i.e. the next room a user will enter in office building [0]	Artificial Neural Networks	Manual location recording on PDAs	Comparison of several prediction techniques; Predicting not only future locations, but the duration of stay at and the locations and the time of the location change	Manual location recording; Impossible to predict future locations in new areas; Applicable solely on indoor places or other places with the clear space division
General	Any, but tested on data about vehicles movement data [0]	Clustering, similarity measuring	GPS (INFATI data)	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
People	Improving robot's behaviour in populated environments by keeping track of people and predicting their movement [0]	HMM, Clustering	Laser-range finders	Long-term prediction; Maintaining and estimating positions of multiple persons; Complete solution (from data collection to prediction)	Clustering depends on trajectory length; Impossible to predict future locations in new areas
Animals	Prediction of wolf kill-sites for gaining insight into predator-prey dynamics [0]	HMM	GPS (collars and manual recorded from aircraft)	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; Manual prey location recording

3.1. Objectives

We believe that considering geospatial conditions (e.g. type of a habitat, climate, and various object vicinity) that pertain to the location and temporal conditions (e.g. season, time of the day) leads to a more accurate description of moving objects behaviour and prediction of their future movement [18]. 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 [16]. Similarly, knowing time attribute, attributes such as season, temperature or rainfall can be get from historical data collected by weather stations.

We propose adaption of existing methods 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.

Another possible improvement could be in supplementing prediction process with expert knowledge about particular moving object characteristics and behaviour.

3.2. Generic Model for Moving objects Movement Prediction

The schema of prediction process that consists of creating the model, learning and finally predicting the movement is given in Fig. 1. “The model” here refers to the prediction model constructed using different prediction techniques and adaptable to the given data about moving objects (e.g. historical data, expert knowledge data, geographical data).

In the first phase, with a help from experts in an application domain, the problem is modelled (for example space partition and/or expert movement rules are defined). The gathered historical data is prepared (using for example clustering techniques, with additional removing of outliers, errors in data or random movement). They are eventually used to define model structure as well (using for example clustering methods to extract interesting places and then to define the parts of model). The historical data is (iteratively) used to estimate the model parameters. Further on, additional information such as terrain or climate characteristics is included in modelling and/or data preparation. The result of the first phase is a model, automatically adapted to the application domain, i.e. to the given data and knowledge representing certain class of moving objects.

In the second phase, the prediction is done based on the given test data by using prepared model and appropriate algorithms. Test data is the part of the historical data, not included in building the model, left to measure and improve model accuracy. As well as historical data, it is prepared to fit the model input. Predicted locations are compared to actual locations stored in test data and model accuracy and statistics is calculated. Test data can be used to tune model parameters.

In the third phase, the prediction is done for given new data using the prepared model and appropriate algorithms. Information about accuracy (calculated in the previous phase) is provided to the user. New data can be used to tune model parameters. Presence of particular process elements differs for various applications. For example, expert knowledge or additional information could be included just to formulate problem or it could be used in an iterative process of parameters estimation. They don't have to be included at all, but that will lead to the loss of model completeness and model accuracy.

The main idea is to automate this process, which encompasses automated fetch of additional information using different services, discovery of expert knowledge from additional data sets (e.g. rule mining), embedding expert knowledge without model perturbation and the independence of application area.

3.3. Data Model of Moving Objects

In order to encompass all additional characteristics of moving objects, we present data model of moving objects in general (Fig. 2 – Rectangle represents entity; diamond shape relationship; symbol 1-N represents one-to-many and N-M many-to-many relationship). All moving objects share mentioned characteristics, although some of them are more important to some types of moving objects, especially in specific prediction process.

The central data in the data model is moving object – representing unique instance of certain class (moving object type) of moving objects. Both moving object and moving object type have properties characteristic to the object/type. Moving object can be seen during observation (that could mean that object is seen, heard, object's trace is seen or location of the object is collected from GPS device). Both time and location (mostly coordinates) are recorded. Location at certain time has certain weather conditions described by weather type entity. Further, locations are parts of areal (region) which can have various characteristics and semantics. Areal can represent the geographical region of for example forests or cities, humid zone etc. The main groups of areal characteristics are: vegetation, climate and urban environment. Some areal can have special meaning to the moving object, such as "home" or "work" regions.

Regardless to which object is of our interest, it can be modelled by data model presented in Fig. 2, with the difference just in object parameters.

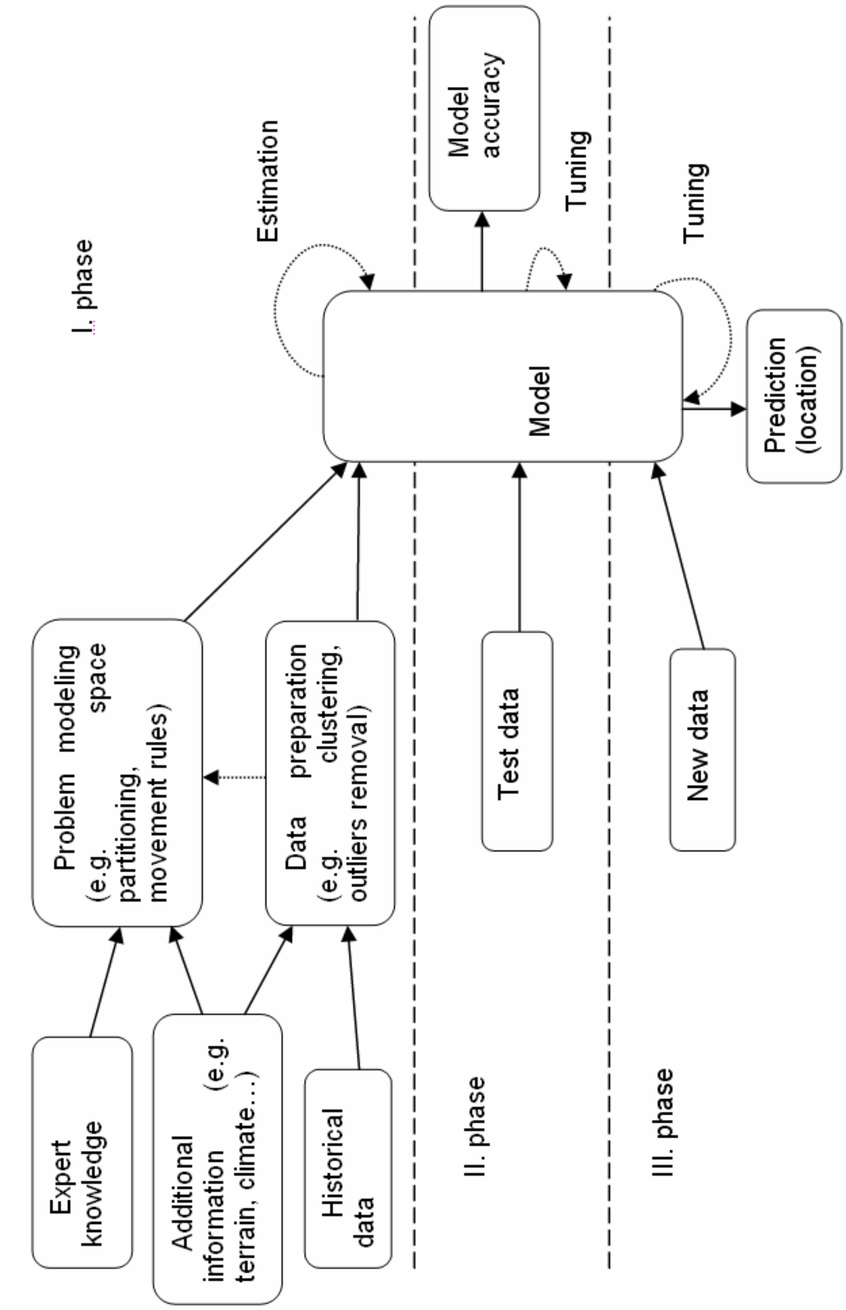

Fig. 1. A schema of moving object's movement prediction process

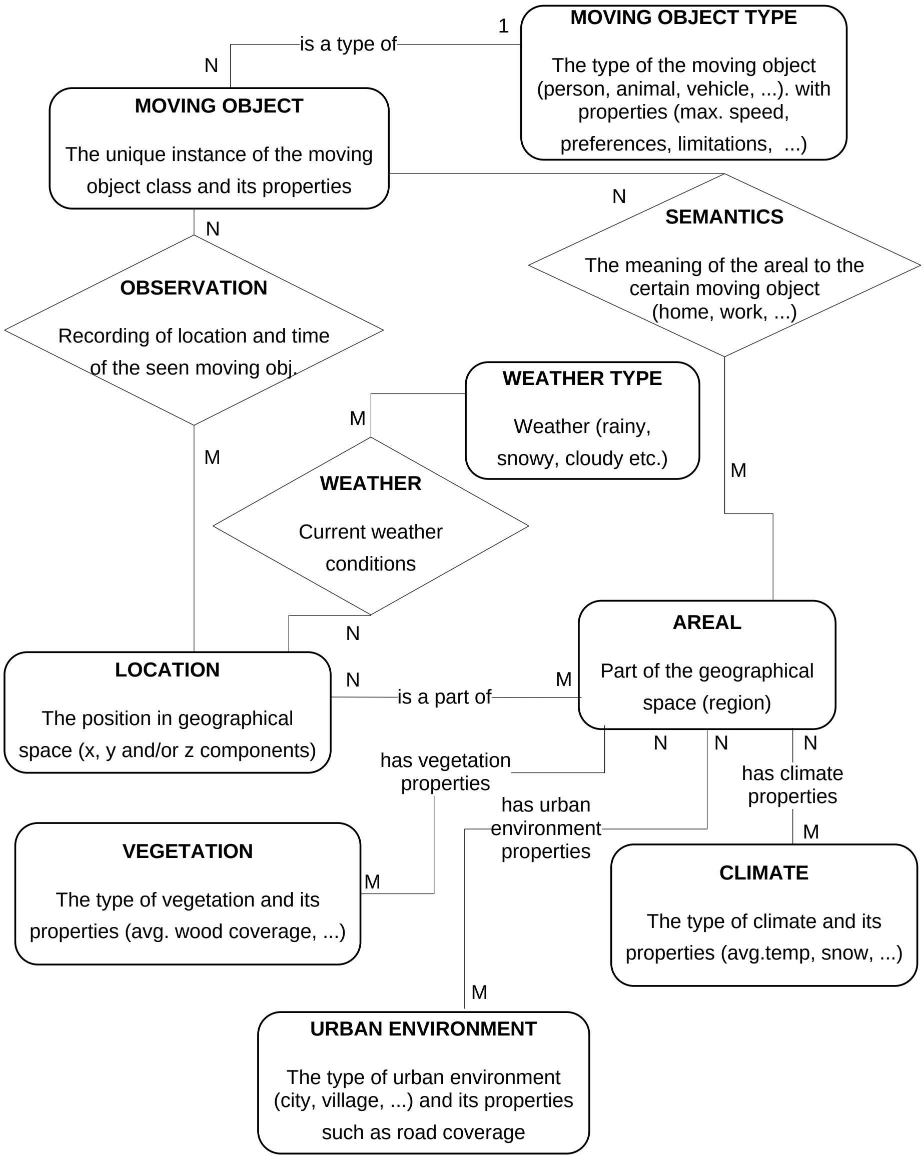

Fig. 2. Data model of moving objects

4. Case Studies

To illustrate the prediction process presented in Fig. 1, we have chosen three case studies: prediction of the future location of vehicles, people and wild animals. We have chosen aforementioned types of moving objects in order to show their differences and to show how the process can be applied to all of them.

We will present one possible method and algorithm selection scenario for each of case studies and shortly discuss about other possibilities.

4.1. Case Study 1 – Vehicles

The first example is prediction of the next location of the vehicle. The main characteristic of vehicles is that they move within the road network. The location of the vehicle equipped with GPS device can be received almost continually (for example, every second).

Since drivers (or people in general) have habits and tend to follow the similar routes [8], it is reasonable to expect some regularity in their movement. Parts of driver's trajectories are overlapping and we expect prediction according to historical locations to be better than just random guessing.

Prediction process is shown on the example of Markov model [22].

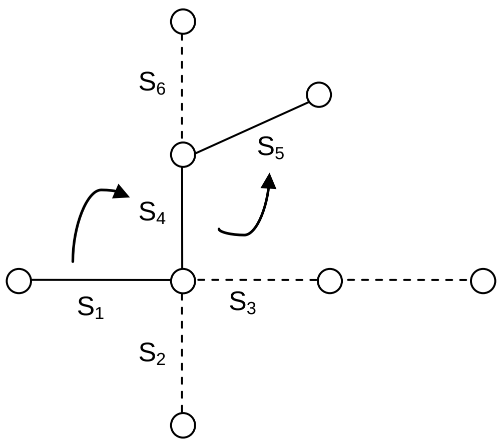

Fig. 3. Vehicle is moving within the road network – all the lines represent road segments, filled lines (states of the model S1, S4 and S5) represent the actual movement of the vehicle

In the first phase of prediction process, according to the knowledge about the road network (additional information), road segments are chosen as Markov model states (S_1, S_2, .. – see Fig. 3). Information about driver's previous movement (historical information) is used to define transition probabilities of the model. Similar approach is presented in [14].

Additional information such as the characteristics of road segments, knowledge about the position of driver's home, work etc. (additional information) and information about characteristics about the vehicle such as maximal and average speed (expert knowledge) could give the better insight of driver's intentions and thus could lead to more accurate prediction.

In the second phase, depending on the chosen model, accuracy of predicted location is differently defined. Accuracy of the model in this case should be compared to the accuracy of random guessing.

Another possible modelling method is presented in [5]. However, there is no additional information or expert knowledge used in both [14] and [5].

4.2. Case Study 2 – People

Unlike the vehicles, people are moving more freely in the space. Although they are moving along the street, they can cross the square, park etc. Position of the person is provided by mobile phone equipped with GPS or more often by the identification of close access points and calculation of person's approximate position. That complicates identification of the road that person is moving along, and model presented in 4.1 is not usable.

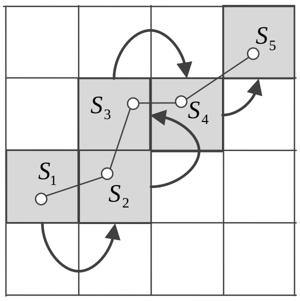

Fig. 4. Person is moving in the space – lines represent actual movement of the person (states of the model S_1, S_2, S_3, S_4 and S_5)

Prediction process is shown on the example of Markov model, but unlike in 4.1, space is partitioned in equally sized cells, which become states of the model (see Fig. 4). Cell size is chosen according to the characteristics of moving object (such as maximum speed) in order to make transitions possible only between neighbouring cells. Similar approach is presented in [11] [19].

States of Markov model could be enriched with additional information such as information about the type of the terrain that pertains to the state of the model. Based on the knowledge about the person's movement preferences (for example it is more likely that person crosses a square than a loan), this could be used to identify transition probabilities.

Another possible modelling method is presented in [27]. Methods like the one presented in [5] can also be used.

4.3. Case Study 3 – Wild Animals

Wild animals are moving even more freely in the space. Another problem is that locations of moving animal are received in sparse intervals (for example every 6 hours). Due to mentioned problems, neither model proposed in 4.1 nor 4.2 is appropriate for this kind of moving objects.

Prediction process is shown again on the example of Markov model.

In the first phase of prediction process, based on historical data and/or expert knowledge, states of Markov model are defined, using for example clustering algorithms to discover frequent regions (see Fig. 5). Interesting regions could also be chosen according to spatial characteristics (additional information), not only based on historical data.

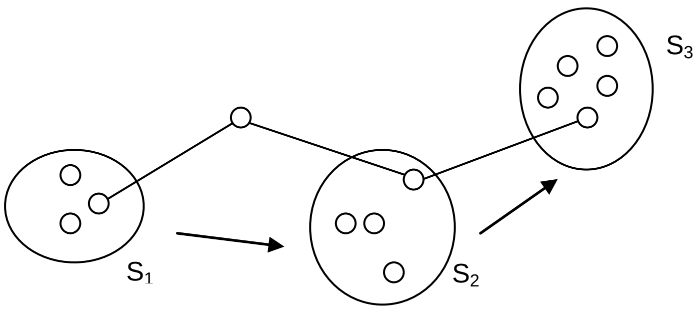

Fig. 5. Wild animal is moving in the space – lines represent actual movement of the animal (states of the model S_1, S_2 and S_3 – chosen as frequent regions)

Additional information (geographical) could be used to get better insight into the meaning of frequent regions and to calculate transition probabilities as well. Further, patterns and association rules could be extracted according to historical or additional information.

As far as we know, such approach has not been described in literature regarding to this type of moving objects. Idea for this approach is based on [1].

4.4. Discussion

Different types of moving objects have different characteristics, but they all move in space with spatial characteristics and their movement has certain characteristics presented in Fig. 2. We suggested possible modelling methods for movement prediction for three different types of moving objects, based on their characteristics. Despite of their differences, movement prediction process is satisfying presented model (Fig. 1).

For example, given the historical locations of vehicle, underlying road network information, locations of driver's home and work, expert knowledge about behaviour of people (such as: "people tend to follow the same route every day, rather than the shortest one"), model will adapt to the model presented in 4.1. If the road network information is not available, model will adapt to the solution similar to the one presented in 4.2. Furthermore, if the locations of home and work are not provided, model could try to identify them based on historical locations.

To conclude, what we claim is that given the all available information about the observed moving object, generic model presented in Fig. 1 could adapt to the given information and according to them provide the most appropriate prediction model. Naturally, if less information is given, model will be more general (probably less accurate, too). If more information is given, model is more specific, adapted to the specific kind of data and more accurate.

5. Conclusion and Future Work

Knowing moving objects behaviour and predicting moving objects future locations can be very useful in many application areas. 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 position.

Short overview and comparison of related work is given, in order to encompass main characteristics of moving objects and to address present problems. Conceptual model for moving objects movement prediction is presented. The directions for future work are to include the knowledge about the type of a habitat that pertains to the location and the knowledge about moving objects' behaviour. The main goal of our future work is to suggest mechanisms to incorporate those elements to a proposed generic prediction model.

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