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A review of map-matching algorithms

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Abstract
The public transport system is a key factor for the development of cities and for the satisfaction of citizens. For this reason, public transport management systems based on IT solutions were created. One of the problems that arise in public transport planning is tracking vehicle routes when using GPS information with signal interruptions or erroneous data. In these cases, it is necessary to implement some map-matching algorithms to solve these problems and follow the correct route for good information of the citizens waiting in the stations and for tracking the routes. This work aims to present the main map-matching algorithms and compare them, highlighting their utility and efficiency.

Keywords: Algorithms, public transportation, map tracking

1. INTRODUCTION

Public transportation is a phenomenon that plays an important role in the social and economic development of a country. Its main purpose is to satisfy the modern man's need for movement. If we analyse its advantages, we notice that it is cheaper than individual transportation and that it provides easy and efficient access to the health system, to education and it gives citizens the opportunity to go to work and other places of public interest. We can say that the public transportation system contributes a lot to the development of modern cities.

To increase efficiency, public transport management systems based on IT technologies (PTMS) have been developed. In addition to material profitability, the use of these systems leads to passenger satisfaction, increased willingness to use public transportation, reduced traffic, reduced environmental impact, and a more accurate forecast of vehicle arrivals at stations. An effective PTMS will take into account route planning that will reduce costs, transport time and waiting time at stations, avoid accidents by monitoring driver behaviour and thus reduce the number of cases when the driver violates traffic rules. Intelligent transportation systems have to calculate transportation utility in order to help traffic planning and management. To build a smart and sustainable transportation system, the methods used are essential if we intend to analyse the transportation utility in a comprehensive way, with innovative technologies and effective communication systems [6].

People want to know the real-time location of vehicles. Information about vehicles can be stored on the server or in the cloud and passengers can access this information through a web application. The map-matching algorithms have as input data the GPS positions of the vehicles and as output data the "real" routes between specified locations obtained by projecting the candidate points on the street map using intelligent methods. Since GPS devices transmit information at different frequencies and levels of accuracy, an elaborate map-matching model must be implemented with the incoming data. Therefore, this paper proposes a review of map-matching algorithms for processing data obtained from GPS devices with low recording frequencies [32]. There are some previous works reviewing map-machining algorithms [7, 21, 29] and our work wants to continue this idea.

The work contains three sections. In the first part, we will define the problem and list the difficulties that may arise when trying to solve it. The second part is a review of the map-matching algorithms highlighting the advantages and disadvantages of each one. The last is a conclusion section.

2. PROBLEM DEFINITION

Vehicle tracking information is represented as a sequence of spatio-temporal points that simulates the trajectory of the moving vehicle. A trajectory *P* consists of a number of *n* points on a map observed in the time interval $[t_0, t_n]$. Each point obtained from GPS is a 4-tuple (*ID*, *x*, *y*, *t*), where *ID* is a vehicle identifier (*x*, *y*) is a point on the map defined by latitude and longitude, and *t* is a moment in time. The coordinates (*x*, *y*) in a GPS record are actually imprecise due to measurement error caused by the limited GPS accuracy. The typical measurement error is in the range of 1-15 m. In certain situations (shadowed and reflected signals), the position recorded in *P* may differ from the actual location by an error of up to hundreds of meters [11]

A map-matching algorithm uses data from GPS systems, selects a series of candidate points and processes this information to obtain the best solution for approximating the exact route of a vehicle (Figure 1).

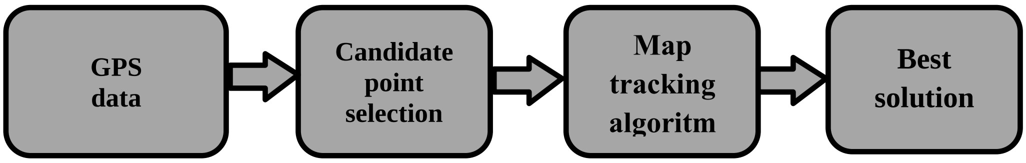

Figure 1. Diagram of determining the exact points on the vehicle route

The street network can be viewed as a directed graph *G* = (*V*, *E*), where *V* is a set of nodes (representing intersections or important points on the map) and *E* is a set of arcs (which are the streets/roads between the points from the map). The graph *G* is the mathematical representation of the street map of an certain area or of an entire city.

The candidate point is the point that is obtained by projecting the GPS point on the road map represented by the graph *G* = (*V*, *E*), which is inside the GPS error zone. The GPS error zone refers to the area where the actual position of a vehicle can be located with an acceptable, a priori established error.

Low frequency GPS recording is a sequence of points received from the device at a lower frequency than normal such that the time interval between two successive points in the sequence is significantly longer than usual. In this case, there are street segments that are not marked by points recorded by the GPS device

The map-matching algorithm is the method of matching the known points on the map with the candidate points p_i, $1 \leq i \leq n$, and of reconstructing the route of the vehicle [19].

Errors that can occur when matching maps are qualitative or quantitative. Qualitative error refers to the context of the move. Unrealistic entries for a map-matching algorithm lead to data indicating: very high speed, very high acceleration, the existence of a vehicle in more than one place at the same time. These unrealistic records may appear due to measurement errors, incomplete information on the road network or its complex topology, violation of traffic rules by the driver (driving on prohibited roads). Quantitative error refers to the number of points not recorded by the GPS measurements assuming that the map is complete. We can use the Levenshtein distance to determine the number of mismatches between the measurements and the actual route on the map. [4, 23] explains how GPS errors can be minimized by trying to find the most suitable candidate points on a route.

Map-matching algorithms must take into account: the sources of errors, the route segments for which the data is transmitted, matching at the segment level, the way of choosing between two matches in conflict, filling the free spaces on the route, the reconstruction of the vehicle route.

3. MAP-MATCHING ALGORITHMS

Due to its practical importance, attempts to solve the map-matching problem have appeared since the 1990s. At that time [13] proposed a simple algorithm based only on the shape of the road segment. It was an efficient algorithm in terms of computation time, but it was not very accurate in the case of intersections and parallel roads. The EKF algorithm based on the topological analysis of the road network using speed and direction information was proposed in [20]. The approach takes a weighted average of two vehicle position determinations based on topological information.

In [26] an Android application is used to locate buses. The application displays the location of the bus and, if there are changes to the route or number of the bus, notifications about the bus number and the location of the bus on Google Map are sent.

An original idea based on genetic algorithms and dynamic programming was described in [19]. Dynamic programming was chosen to speed up the computation of the fitness function, and dynamic time fitting is used to assess the geometric similarity between the recorded trajectory and the observed trajectory. The method has been verified with real data and good results were obtained both in terms of accuracy and calculation time, especially considering that calculation time is a problem for most algorithms that process GPS data.

[31] proposes an algorithm that analyses the entire GPS trajectory and divides it into several segments. The best match is found for each segment. The algorithm in [11] is based on the leapfrog method to avoid intermediate points between two intersections in order to save computation time, and thus the efficiency of the classic algorithm is increased. This algorithm was then supplemented with the MapReduce method and run on the Hadoop platform to take advantage of parallel computing by further decrease the computation time and the time required for input/output operations. To preserve data confidentiality, storage is done in both public and private clouds.

We can look at the data that defines the trajectory as a set of random variables of a stochastic process. For this reason, an approach based on Markov chains seems very suitable because it does not require a huge amount of training data. An important direction of research has been that based on Markov chains [12]. Hidden Markov Models (HMM) typically use historical data to find transition probabilities between road segments. The algorithm in [9] is based on HMM and uses location and direction to find the right candidate on the path. [18] presents a HM Model based on map-matching algorithm with particular emphasis on the cases of location data that are geometrically noisy or temporally sparse. [15] approaches the Multiple Candidate Matching (MCM) method to increase the quality of map matching. This method stores multiple candidates from those for which there was a match in the historical data. Limited number of provided candidates are generated in real-time to decrease the computation time. The choice is made between historical candidate points and those obtained in real time [8]. [1] proposed a hidden Markov map-matching model (EHMM) using traffic rules, historical information and the road network topology. [16] describes an HMM algorithm using mobile phone positioning and GPS data. The algorithm uses the topology of the network, geometric information and the relativity between the candidate points and the positioning points for the Markov process, and methods for finding the Viterbi path with the best possible probability. A spatio-temporal matching (STD-matching) algorithm for small-sample GPS transmissions is described in [8]. The algorithm takes into account distance and map topology information, speed restrictions on different road segments, direction of movement. Experiment results show that STD matching algorithm outperforms other existing algorithms in terms of matching accuracy. The experimental results show that the STD matching algorithm performs better than the ST matching algorithm [17, 33] and the stMM algorithm [22]. Also the ST-Matching algorithm works better than incremental algorithm and global map-matching algorithm based on Average-Fréchet-Distance. The stMM algorithm starts from A^* algorithm to obtain the shortest path between two points, taking into account both the distance along the shortest path and the distance along the vehicle trajectory. [25] presents the trendHMM algorithm that incorporates the movements of neighbouring data in the matching process and introduces the concept of a window that contains adjacent geo-location information. trendHMM can use relationships between geo-location data and reports better results than other HMM algorithms.

[30] comes with an algorithm based on Markov decision processes combined with reinforcement learning algorithms and with a trajectory simplification algorithm. The algorithm evaluates direction changes in routes, which reduces detours and round trips in the results. This algorithm is provided open source.

Some approaches are based on advanced mathematical theories such as: geometry [5], neural networks [14], fuzzy logic [27], Kalman filter [3, 24], Dempster-Shafer theory [34]. These algorithms, although they seem revolutionary, are difficult to put into practice.

[10] propose the ANM algorithm which they describe as an online adaptive map-matching algorithm. AMM filters out poor quality GPS points and proposes a correction mechanism to improve accuracy.

4. CONCLUSIONS

Due to the practical importance of the problem, in this paper we have chosen to review the methods for solving the map-matching problem. We have listed the existing challenges and shown how they can be avoided. We believe that the paper reveals the current state of research and can suggest future work directions.

Most algorithms for map-matching are based on Hidden Markov Models and are differentiated by variations that increase accuracy or calculation speed. Hidden Markov Models are used when a path must be chosen from several possible ones. HM models are suitable for processes that involve choosing a path through many possible states. The HMM states represents the road segments and we want to make the correspondence between each measurement and the correct road segment. Measurement probabilities can be viewed as the possibility that a state will result, based on that measurement alone.

Other algorithms based on advanced mathematical methods (geometry, fuzzy logic, neural networks and so on) can sometimes be difficult to put into practice.

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