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Map Matching Algorithm Based on a Hidden Markov Model for Vehicle Navigation

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ABSTRACT

Map Matching Algorithm plays vital role in today vehicle navigation technology. This paper deals with functionalities of Map matching Algorithm based on Hidden Markov model for vehicle navigation using GPS. The main objectives this paper is to gain knowledge about Hidden Markov Model. Hidden Markov Model is mainly focused on Statistical Model with two states, one as Observed State and Unobserved State (Hidden State). In Hidden Markov Model, the State which is not directly visible, but result is mainly focus on the output state which is visible. Probability Distribution of Each State will produce possible output tokens. Token are sequenced which are generated by Hidden Markov Model provides information about the state with sequence. The Main adjective of hidden refers to the sequence of state through model which passes, not as parameter to the model, but model still referred as a hidden Markov Model even if exactly Known Parameter.

Keywords: *Map Matching Algorithm, GPS, Hidden Markov Model*

1. INTRODUCTION

The Process of Map Matching Algorithm can be classified into three categories to find out the position of particular object or vehicle. Macro scale: Navigation usually performs the task of finding a particular path between two nodes in the network consisting of link. Micro scale: Typically consider navigation at the vehicle and is concerned with task such as lane keeping as well as detecting and avoiding obstacles. Mesoscale: which is a level in between micro scale and macro scale, consider vehicle operation at link level. Form a Navigation point of view, mesoscale route planning is generally concerned with vehicle such as passing, pulling off the side of the roadway, moving out of the way of emergency vehicle, merging in and out special (Manikandan et al., 2017) .

Hidden Markov Model (HMM) is a statistical Markov model in which the system being modelled is assumed to be a Markov process with unobserved (i.e. hidden) states. The Hidden Markov Model is a finite set of states, each of which is associated with a (generally multidimensional) probability distribution. Transitions among the states are governed by a set of probabilities called transition probabilities. In a particular state an outcome or observation can be generated, according to the associated probability distribution. It is only the outcome, not the

state visible to an external observer and therefore states are ``hidden" to the outside, hence the name Hidden Markov Model.

2. BRIEF REVIEW OF MAP MATCHING ALGORITHM

Map Matching Algorithm is mainly used to control and monitor the vehicle in the Urban Areas which may leads avoid traffic, accidents and also reduce the time taken from one place to another place. (Manikandan et al., 2017) The eight based processes of Map Matching algorithm are a) weight based map matching algorithm has three steps: initialization, same-segment, and next-segment. Distance between the GPS point and road segments, difference between the heading of the GPS point and direction of road segments (Greenfeld J.S et al., 2002). The difference between the direction of consecutive GPS points and direction of road segments are used to identify the best segment among candidates near intersections. The weight of each criterion in this algorithm is dynamic. The weights of criteria are calculated for each GPS point based on its: (1) positional accuracy, (2) speed, and (3) travelled distance from previous GPS point. b) Enhanced Based map matching algorithm In dense urban areas it is still difficult to obtain good positioning using a single technology. This problem has led to the introduction of combining multiple positioning techniques. Intelligent Urban Positioning (IUP) is based on combining positioning algorithms augmented with three dimensional mapping techniques for distinguishing between non-line-of-sight (NLOS) and line-of-sight (LOS) signals and multi-constellation GNSS, using signals from all visible satellites. c) Enhanced, Weight Based map matching algorithm has the potential to be applied in a range ITS services with a low polling frequency positioning data. This enhanced MM algorithm is fast, simple and very efficient and therefore, has the good potential to be implemented by industry, especially in city with intricate road network. d) Fuzzy Based map matching algorithm compares the road membership value of candidates by fuzzy sorting, and adjusts the measure coefficient to improve the accuracy of map matching. e) Hidden Markov Based map matching algorithm is a Markov process comprising a number of hidden (unobserved) states. Transitions between states can occur with a certain probabilities. Each state is assigned with a set of observations. One of them is to be output, as the state is reached. f) Activity of Edge Based map matching algorithm: The Existing map-matching algorithms are not suitable for the low-frequency FCD (floating car data). By analyzing local map-matching algorithms and global map-matching algorithms, and overall considering the FCD trace, a map-matching algorithm for low-frequency FCD based on improved AOE (activity on edge) network was proposed. g) Distributed Based map matching algorithm main idea is to reduce the algorithm running time by distributing the processing across multiple working nodes. Each trajectory point is a position that must be mapped to a corresponding point in the road network. Considering GPS precision errors, the nearest point is not necessarily the correct one. h) Offline Based map matching algorithm can take the advantage of not only matching each point according to past data but also based on the following “future” point, which helps the algorithm to select the correct road near to junctions. The literature review made by (Shenjingwei et al.,2015) states that the majority of the existent algorithms are for real-time applications, since the demand here is higher than in post-processing ones. In fact, only one offline algorithm is presented. We

mainly classified process of Map Matching algorithm as feasibility study, which is mainly implemented in the Urban Cities.

3. HIDDEN MARKOV MODEL – MAP MATCHING ALGORITHM

Hidden Markov Model is mainly focused on Statistical Model with two states, one as Observed State and Unobserved State (Hidden State). In Hidden Markov Model, the State which is not directly visible, but result is mainly focus on the output state which is visible. Probability Distribution of Each State will produce possible output tokens. Token are sequenced which are generated by Hidden Markov Model provides information about the state with sequence. The Main adjective of hidden refers to the sequence of state through model which passes, not as parameter to the model, but model still referred as a hidden Markov Model even if exactly Known Parameter.

4. PROBABILISTIC PARAMETERS OF A HIDDEN MARKOV MODEL

The object of a Hidden Markov Model is to model the state sequence over time. The state space for a HMM model includes a finite set of states, each of which is associated with a probability distribution. The transitions among these states are governed with a certain probability which is referred as state transition probability. In any state, an observation can be generated with certain probability, which was called emission probability. However, the actual state is not externally visible, which explains the appellation "hidden" Markov model.

x – States (x1,x2 and x3)

y – Possible Observations (y1,y2,y3 and y4)

a – State transition probabilities (a12, a21 and a23)

b – Output probabilities (b11, b12, b13, b14 and etc..)

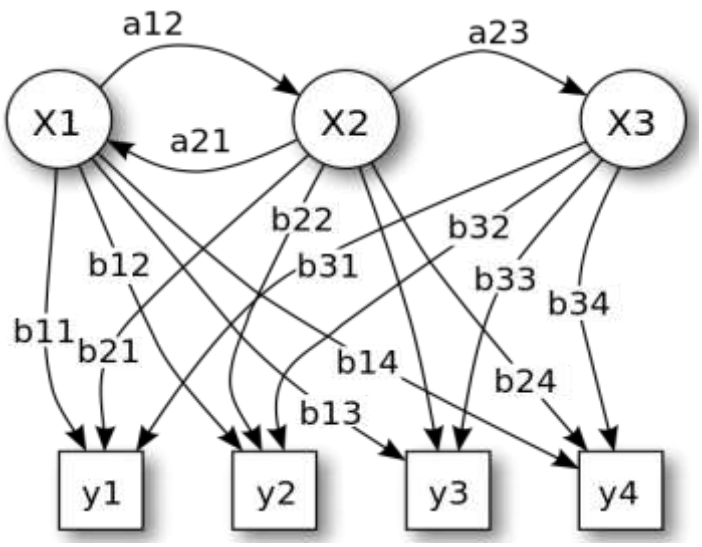

Fig.1. Probabilistic Parameters of HMM

5. PROBABILITY OF AN OBSERVED SEQUENCE

The task is to compute in a best way, given the parameters of the model, the probability of a particular output sequence. This requires summation over all possible state sequences:

The sum runs over all possible hidden-node sequences (L- Length)

$$X = x(0), x(1) \ldots\ldots, x(L-1)$$

6. PROBABILITY OF THE LATENT VARIABLES

A number of related tasks ask about the probability of one or more of the latent variables, given the model's parameters and a sequence of observations.

6.1. Filtering

The task is to compute, given the model's parameters and a sequence of observations, the distribution over hidden states of the last latent variable at the end of the sequence. This task is normally used when the sequence of latent variables is thought of as the underlying states that a process moves through at a sequence of points of time, with corresponding observations at each point in time. Then, it is natural to ask about the state of the process at the end. This problem can be handled efficiently using the forward algorithm.

6.2. Smoothing

This is similar to filtering but asks about the distribution of a latent variable somewhere in the middle of a sequence. This can be thought of as the probability distribution over hidden states for a point in time k in the past, relative to time t. The forward-backward algorithm is an efficient method for computing the smoothed values for all hidden state variables.

6.3. Joint Probability

The joint probability of the entire sequence of hidden states that generated a particular sequence of observations. This task is generally applicable when HMM's are applied to different sorts of problems from those for which the tasks of filtering and smoothing are applicable. This task requires finding a maximum over all possible state sequences, and can be solved efficiently by the Viterbi algorithm.

6.4. Statistical Significance

Statistical significance is the probability that a sequence drawn from some null distribution will have an HMM probability (in the case of the forward algorithm) or a maximum state sequence probability (in the case of the Viterbi algorithm) at least as large as that of a particular output sequence. When an HMM is used to evaluate the relevance of a hypothesis for a particular output sequence, the statistical significance indicates the false positive rate associated with failing to reject the hypothesis for the output sequence.

6.5. Viterbi Algorithm

The Viterbi algorithm is a dynamic programming algorithm for finding the most likely sequence of hidden states called the Viterbi path that results in a sequence of observed events, especially in the context of Markov information sources and hidden Markov models. In a HMM, the state is not directly visible, however variables influenced by the state are visible. Each state has a probability distribution over the possible observations. The state of the system mutates from one state to another with a certain probability described by the state transition probability. Meanwhile, estimated locations (GPS measurement or other mobile positioning results) are the visible observation layer and correct road links are the invisible state layer. The vehicle moves on road links from one to another during certain time period with certain probability. Given the characters of the map-matching and HMM model, we applied the Viterbi algorithm to estimate the sequence of road links based on observed GPS positions in this study.

7. BASIC PROBLEMS OF HIDDEN MARKOV MODEL

Once we have an HMM, There are three problems of interest.

1) Evaluation Problem: Evaluation problem can be used for isolated Path recognition.
2) The Decoding Problem: Decoding problem is related to the continuous recognition as well as to the segmentation.
3) The Learning Problem: Learning problem must be solved, if we want to train an HMM for the subsequent use of recognition tasks.

8. MAP MATCHING WITH HMM ON GPS POSITIONING

The first test deals with a set of GPS data with approximate 28 km along its trajectory. Sample rate of the data is 0.5 Hz. The visualization of the Viterbi path, which is represented by blue links. A statistical analysis indicates that the HMM-based map-matching have high efficiency and accuracy than other map-matching methods. At the same time, certain road links which do not belong to the true trajectory were also selected, only because the project distance from a GPS point to these road links is shorter. Short road links are missed because the project distance from the GPS point to these links is longer than the project distance between the GPS points and their neighbours. The visualization of these missing short road links. Map-aiding operation aims to query regarding missing road links related to the Viterbi path, eliminate superfluous road links, reconnect the road links and get the map-matching result.

9. CONCLUSION

It concludes that Map Matching Algorithm based on a Hidden Markov Model is mainly focused on Statistical Model with two states, one as Observed State and Unobserved State (Hidden State). In Hidden Markov Model, the State which is not directly visible, but result is mainly focus on the output state which is visible. Probability

Distribution of Each State will produce possible output tokens. Token are sequenced which are generated by Hidden Markov Model provides information about the state with sequence.

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