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Vehicular Route Prediction In City Environment Based On Statistical Models

Prof.Uma Nagaraj, Ms.Nivedita Kadam
Computer Dept. MIT, AOE MIT.AOE, Alandi(D) Pune, India
Computer Dept. MIT, AOE MIT,AOE, Alandi(D) Pune, India

Abstract
Travel route analysis and prediction are essential for the success of many applications in Vehicular Ad-hoc Networks (VANETs). It is challenging to make accurate route prediction for general vehicles in city settings due to several practical issues such as very complicated traffic networks, the highly dynamic real-time traffic conditions and their interaction with driver's route selections. The traffic conditions on complicated road networks keep changing from time to time. Inspired by the observation that a vehicle often has its own route selection flavour when traversing between its sources and destinations, here it defines a mobility pattern as a consecutive series of road segment selections that exhibit frequent appearance along all the itineraries of the vehicle. Here with the help statistical models like Markov Model with only first order Markov Model (MM) to choose only the next intersection point of the road segment with only one pattern without considering traffic conditions again by using the Hidden Markov Model(HMM) to predict next intersection point by considering traffic conditions with shortest distance and obstacle and Variable-order Markov Model (VMM) to select mobility patterns from the source to destination which is chosen by the driver by considering the traffic conditions .
Keywordrs- MM, HMM, VMM, RSU, OBU.

I. Introduction

A wireless ad hoc network is usually defined as a set of wireless mobile nodes dynamically self-organizing a temporary network without any central administration or existing network infrastructure. Recent advances in wireless technologies and dedicated short-range communications technologies have made inter vehicular communications (IVC) and road–vehicle communications (RVC) possible in mobile *ad hoc* networks (MANETs).[11] This has given birth to a new type of MANET network known as the vehicular *ad hoc* network (VANET). Internetworking over VANETs has been gaining a great deal of momentum over the past few years. Its increasing importance has been recognized by major car manufacturers, governmental organizations, and the academic community. They resemble to MANET networks in their rapidly and dynamically changing network topologies due to the fast motion of vehicles. However, unlike MANETs, the mobility of vehicles in VANETs is, in general, constrained by predefined roads. Vehicle velocities are also restricted according to speed limits, level of congestion in roads, and traffic control mechanisms (e.g., stop signs and traffic lights)..

As the rapid development of wireless technology, more and more studies on vehicular ad hoc network (VANET) are trying to build innovative applications to provide safety and comfort for passengers and drivers, such as fast dissemination of warning messages of traffic accidents, congestion avoidance, sharing media between vehicles and onboard Internet access. To realize these stunning applications, manipulating effective opportunistic wireless communications between different vehicles and vehicles to roadside infrastructure is crucial. For example, two vehicles can communicate with each other in a very short time only when they geographically meet. Therefore, knowing possible locations of vehicles in the future can largely leverage the performance of the whole system. Consequently, it is highly important to accurately predict travel routes of vehicles.

Accurate travel route prediction in urban vehicular environments, however, is very challenging due to the following three reasons.[1]

1. The structure of the City road networks is very complicated.
2. A vehicle may be heading for different destinations.
3. Traffic conditions are time varying and will influence the route decision of a vehicle dramatically.

Motivation of this is to implement such a system which will remove some problems of real time traffic conditions in city environment such as traffic jams, accidents. Route Prediction of a vehicle makes the journey more comfortable and efficient for both the driver as well as the passengers by generating different appropriate mobility patterns for vehicle in VANET.

II. ROAD REPRESENTATION

Here with the use a Markov model to predict a vehicle's near term future route. More specifically, using a discrete Markov chain representation. Applied to our problem, this scheme represents the state of the vehicle as being located on one of a discrete set of road segments, as shown in Figure 1. Road segments come from a map representation of the road network. Segments terminate at intersections here it shows the 9 intersections road segments which are denoted as $I_1, I_2, \ldots, I_9$.

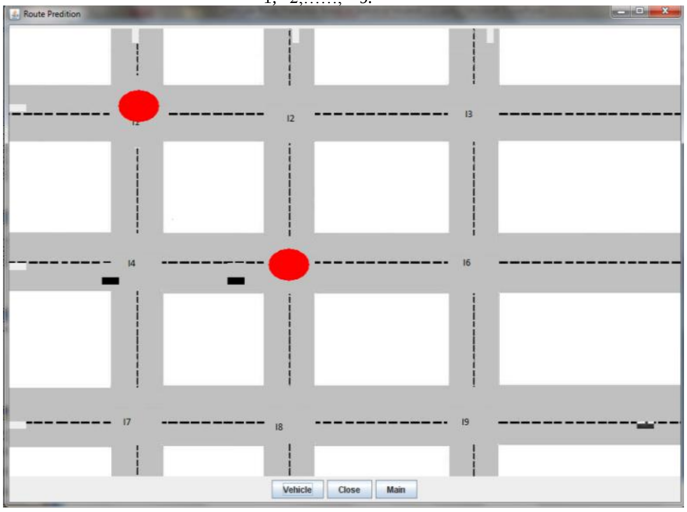

Figure1: Road Representation with traffic conditions

Vehicle motion is not restricted it can move left , right ,up or down to reach to its destination from the source, depending o the drivers route choice. To communicate with the other vehicle here it takes the help of road side unit which communicate with the on board unit which is present in the vehicle. Message is passed from OBU to RSU and RSU send the feedback to OBU of vehicle which helps a driver to predict the next future rode segment with the appropriate choice of the driver comparing the other choices of the road segments. Here each vehicle has three choices to move next road segment. Here we are considering only the forward direction of the vehicle for example form the source i_1 the vehicle can move only in forward to i_2 and i_4 it cannot move back and up.

III. STATISTICAL MODELS

A. *Markov Model[2]*

Markov Model predicts only vehicle's near term future route is based on its near term past route[6]. A Markov model is a graphical statistical model that captures a sequential model of behaviour. It is a tuple $< S,A,T >$, where S is a (finite) set of states, A is a (finite) set of actions, and T is the transition function $T : S\times A\times S\rightarrow R$, where $T(s_i, a, s_j) = p(s_i|s_j, a)$, which is the probability of transitioning to state s_i given that the system is in state s_j and action a is executed. Given a Markov model and an initial state distribution π, one can predict the state distribution that results from carrying out a sequence of actions $<a_1, a_2, ..., a_n>$. If $p^t(s_i)$ is the probability of being in state s_i at time t (where $\pi(.) = \pi^0(.)$ is the initial state distribution), then $p^{t+1}(s_i) = \Sigma s_j \epsilon S\ p^t(s) T(s_i, a^{t+1}, s_j)$. Note that while the exact state of the system is uncertain when doing *prediction*, it is assumed that the state is known for certain after the actions are actually *executed* in the world.

The Markov model can be used to predict beyond just the next road segment. We can clearly build $P\ [(1)|X(0)]$, where x(0) is the current road segment and x(1) is next road segment, which is the distribution over the road segments after the next one, given the current one. We can also user higher order models to make these farther out predictions, *e.g.* $P\ [(2)\ |X\ (-1)\ ,\ X(0)]$. In general, we can build an nth order Markov model ($n \geq 1$) to predict the m^{th} next encountered segment ($m \geq 1$). The general n^{th} order model is denoted as

$$P_n[X(m)]=P[X(m)|X(-n+1),X(-n+2),\ldots,X(0)] \qquad (1)$$

Our Prediction algorithm is based on the statistical map on which number of vehicles are moving on the road.

B. *Hidden Markov Model[3]*

A Hidden Markov model (HMM)[7] is a Markov model with hidden (unobservable) state. An HMM is a five tuple $<$ S,A,O,T,Z,p $>$, where S, A, and T are the same as with the Markov model and p is the initial state distribution. In addition, O is a (finite) set of observations and Z is the observation function Z : O×S×A→R, where Z(o, s, a) =p(o| s, a), which is the probability of receiving observation o given that the system ends up in state s after executing action a. For many problems, Z is the same for all values of a, (i.e., Z(o, si, aj)=Z(o, si, ak)). In what follows, it will use Z(o, s) as shorthand for Z(o, s, a), when Z is the same for all values of a.

C. *Variable Order Markov Model[4]*

VOM models arose as a solution to capture longer regularities while avoiding the size explosion caused by increasing the order of the model. In contrast to the Markov chain models[9], where each random variable in a sequence with a Markov property depends on a fixed number of random variables, in VOM models this number of conditioning random variables may vary based on the specific observed realization, known as context. These models consider that in realistic settings, there are certain realizations of states (represented by contexts) in which some past states are independent from the future states leading to a great reduction in the number of model parameters.

Algorithm for learning VMM over a finite alphabet ∑. Such algorithms attempt to learn probabilistic finite state automata, which can model sequential data of considerable complexity. In contrast to N-gram Markov models, which attempt to estimate conditional distributions of the form P(σ|s), with S Є ∑N and σ Є ∑, VMM algorithms learn such conditional distributions where context lengths |s| vary in response to the available statistics in the training data. Thus, VMMs provide the means for capturing both large and small order Markov dependencies based on the observed data. Although in general less expressive than HMMs, VMM algorithms have been used to solve many applications with notable success.

IV. ALGORITHMS FOR ROUTE PREDICTION

Here in this section we are representing three different algorithms for route prediction.

A. Route Prediction Algorithm using Markov Model

Inputs: Route map in terms of x and y coordinate, Number of Cars, Trained vehicle road segments, speed of the car, source and destination of the journey, n<=1.

Expected Outputs: Pattern Utilization, Prediction accuracy.

1. Create a road map in terms of x and y coordinate.
2. Creation RSU and OBU for each newly created vehicle for communication.
3. Enter the source and destination of the journey.
4. Find all possible intersection points from the database to reach the destination from the source.
5. Select the shortest route from all routes by comparing their lengths.
6. Save the length of that route in to the buffer.
7. Check that intersection point is near to destination point if no go to step 2. Otherwise go to step 6.
8. Return that shortest length to the driver.
9. Count the mobility patterns generated by the vehicle to reach the destination.
10. Stop.

B. Route Prediction Algorithm using Markov Model

Inputs: Route map in terms of x and y coordinate, Number of Cars, Trained vehicle road segments, speed of the car, source and destination of the journey, n<=1.

Expected Outputs: Pattern Utilization, Prediction accuracy.

1. Create a road map in terms of x and y coordinate.
2. Creation RSU and OBU for each newly created vehicle for communication.
3. Enter the source and destination of the journey.
4. If obstacles occurs in between from source to destination count the no. of obstacle and save in the database.
5. Find all possible intersection points from the database to reach the destination from the source.
6. Select the shortest route from all routes by comparing their lengths.
7. Save the length of that route in to the buffer.
8. Check that intersection point is near to destination point if no go to step 2. Otherwise go to step 6.
9. Return that shortest length to the driver.
10. Count the mobility patterns generated by the vehicle to reach the destination.
11. Stop.

C. Route Prediction Algorithm using VMM

Inputs: Route map in terms of x and y coordinate, Number of Cars, Trained vehicle road segments, speed of the car, source and destination of the journey, n<=9.

Expected Outputs: Pattern Utilization, Prediction accuracy. Predict future routes with highest probability.

1. Create a road map in terms of x and y coordinate.
2. Creation RSU and OBU for each newly created vehicle for communication.
3. Enter the source and destination of the journey.
4. If obstacles occurs in between from source to destination count the no. of obstacle and save in the database.
5. Find all possible whole path from the database to reach the destination from the source.
6. Select the less obstacle count route from all possible routes by comparing their obstacle count.
7. Save the obstacle count of that route in to the buffer.
8. Return the less obstacle route to the driver.
9. Count the mobility patterns generated by the vehicle to reach the destination.
10. Stop.

V. PERFORMANCE EVALUATION AND RESULTS

Here we are using the java language for implementation of all three algorithms which are described in section III and all these algorithms are base on statistical map and information of this map is stored in database from which data can be stored and retrieved for the communication between the vehicle. For communication of the vehicle we used the RSU on the road and OBU which is fitted in the vehicle which works like a client and server for request and response for the driver of the vehicle which gives the indication for the driver for the direction to reach from source to destination in accurate time.

As we mentioned earlier MM does not detect any obstacle it gives only the next intersection point .HMM detect First order Markov model which predicts the next intersection point only with all possibilities and chooses the shortest distance without considering traffic condition.

HMM: Hidden Markov model also predict the next intersection point only with all possibilities and chooses the shortest distance by only observing traffic condition.

VMM: Variable order Markov model predicts the whole path source to destination with all

possibilities by considering traffic conditions and on where traffic is less it choose that path for destination. Here as shown in Figure 2 comparison is done on the basis of obstacles and distance and no. of patterns generated by each module.
X axis= Models
Y axis= No. of patterns.
Here MM does not detect the obstacle so in the obstacle graph this model is not showing any no of patterns generated.
It shows only for the HMM and VMM.

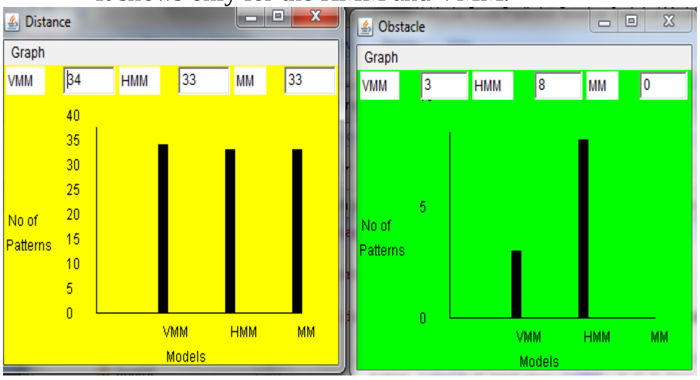

Figure 2: Comparative results of three modules

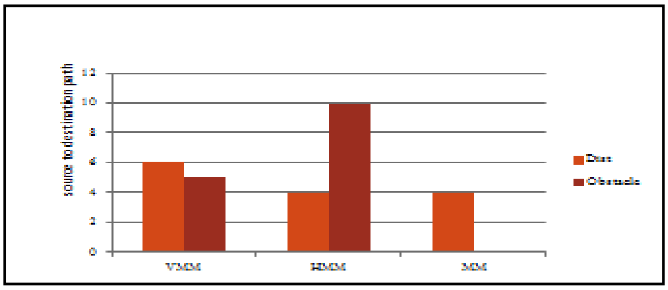

Figure 3: Prediction accuracy comparing between models with

Consideration of traffic conditions with distance and obstacles.
X axis= Models
Y axis= source to destination path.

As shown in the figure 2,3 and 4 our comparative results of three models shows that VMM is having a good approach for predicting the accurate route for the driver from the source to destination.

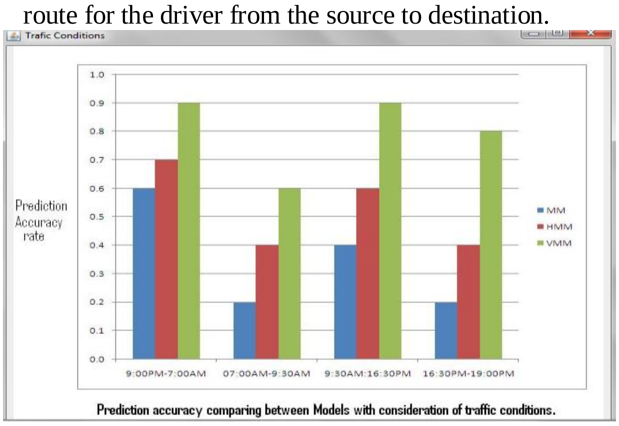

Figure 4: Prediction Accuracy by considering Traffic Condition.

VI. CONCLUSION

Here in this work for each intersection point of a road segments minimum three choices are provided and according to this choices whichever choice is having less distance as compared to the other choice the MM and HMM predicts that choice for the driver and for the VMM which choice is having less number of obstacle that choices is predicted by the VMM.

The mobility pattern generated by the vehicle is more for the MM and HMM because it predicts only the next intersection point from the road map to the driver so more patterns are generated and the mobility patterns generated by the VMM vehicle are less because it predicts the whole path in one step so there is no more confusion for a driver when it uses the VMM for route prediction.

Accurate and efficient Route Prediction probability by considering time factor is more in VMM as compared to the MM and VMM.

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