MOBILITY PREDICTION OF THE VEHICLE USING MARKOV MODEL

[1]Soundarayaa R K, [2] Dr.J.C.Miraclin Joyce Pamila M.E.,Ph.D

[1]PG Scholar, Dept. of Computer Science Engineering, Government College of Technology, TamiNadu, India
[2]Head of the Department, Dept. of Computer Science Engineering, Government College of Technology, TamilNadu, India

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Abstract - *Mobility prediction of vehicle using markov model aims to predict the future location of a vehicle using current and the past information of the same vehicle. Future connected RSU-id of vehicle and the location will be predicted based on the past and the current information of that vehicle. Dynamic markov model which adaptively selects the 1st and 2nd order markov model based on the availability and quality of the vehicle' traces is used in the proposal. The algorithm takes input parameters like obu-id, rsu-id, speed of the vehicle, timestamp, day of the week, current location and date. Using all the above mentioned input data fields the algorithm works to predict the future location of a particular vehicle in the given time interval. The rationale behind using the hybrid markov model is that standard first-order markov chain models are memory less predictors which means next location depends on only the current information but second order considers both the previous and current RSU connections. The use of two state information increases the prediction accuracy.*

1. INTRODUCTION

In the past years, vehicular ad-hoc networks (VANETs) have evolved from a research topic to real-world deployments. VANETs provide car-to-car communications to address the increasing traffic demands for vehicle-correlated applications. Efforts have also been made to explore the potential of using vehicular network communications to improve transportation efficiency and to provide comfortable user experiences to passengers and convenience to drivers. The service characteristics of VANETs differ from conventional wireless communication services, which means that we have to analyse the specific requirements of various vehicles, their services, and applications. A recent study highlights the importance of having a comprehensively coordinated system to meet the low-latency and high-mobility communication features for VANETs. VANETs consist of hundreds of connected vehicles, which use DSRC (Dedicated Short-Range Communications), Wi-Fi, or cellular networks to connect to each other and to the infrastructure. A real-world VANET test bed includes the installation of communication systems, which assure vehicle- to-vehicle (V2V), vehicle-to-roadside (V2R) and vehicle-to- infrastructure (V2I) communications. A VANET is deployed by installing on-board units (OBUs) on vehicles, road side units (RSUs) at particular city spots, and by connecting the RSUs to the access infrastructure (copper or fiber network).

Vehicular Ad-Hoc Network or VANET is a technology that has moving vehicles as nodes in a network for creating a mobile network. We can say that VANET turns each and every vehicle into a wireless node, allowing cars to connect to each other which are 100-300 meters apart and, in turn, create a wide range of network it is a term which is used to describe the spontaneous ad hoc network that is formed over vehicles moving on the roads. Vehicular networks are very fast emerging for deploying and developing new and traditional applications. It is characterized by rapidly changing topology, high mobility, and ephemeral, one-time interactions. Both MANETs and VANETs are characterized from the movement and self-organization of the nodes (i.e., in the case of VANETs it is Vehicles). Vehicular ad-hoc networks (VANETs) are created by applying the principles of mobile ad hoc networks (MANETs) – the spontaneous creation of a wireless network of mobile devices – to the domain of vehicles. VANETs were first mentioned and introduced in 2001 under "car-to-car ad-hoc mobile communication and networking" applications, where networks can be formed and information can be relayed among cars. It was shown that vehicle-to-vehicle and vehicle-to-roadside communications architectures will co-exist in VANETs to provide road safety, navigation, and other roadside services. VANETs are a key part of the intelligent transportation systems (ITS) framework. Sometimes, VANETs are referred as Intelligent Transportation Networks.

1.1 APPLICATIONS OF VANET

VANETs support a wide range of applications – from simple one hop information dissemination of, e.g., cooperative awareness messages (CAMs) to multi-hop dissemination of messages over vast distances. Most of the concerns of interest to mobile ad hoc networks (MANETs) are of interest in VANETs, but the details differ.[5] Rather than moving at random, vehicles tend to move in an organized fashion. The interactions with roadside equipment can likewise be characterized fairly accurately. And finally, most vehicles are restricted in their range of motion, for example by being constrained to follow a paved highway.

Example applications of VANETs are:

- Electronic brake lights, which allow a driver (or an autonomous car or truck) to react to vehicles breaking even though they might be obscured (e.g., by other vehicles).
- Platooning, which allows vehicles to closely (down to a few inches) follow a leading vehicle by wirelessly receiving acceleration and steering information, thus forming electronically coupled "road trains".
- Traffic information systems, which use VANET communication to provide up-to-the minute obstacle reports to a vehicle's satellite navigation system[6]
- Road Transportation Emergency Services – where VANET communications, VANET networks, and road safety warning and status information dissemination are used to reduce delays and speed up emergency rescue operations to save the lives of those injured.
- On-The-Road Services – it is also envisioned that the future transportation highway would be "information-driven" or "wirelessly-enabled". VANETs can help advertise services (shops, gas stations, restaurants, etc.) to the driver, and even send notifications of any sale going on at that moment.

2. MOBILITY PREDICTION:

Mobility predictions have regularly been shown to be a necessity for providing efficient resource management and services in wireless networks: foreknowledge of users' mobility allows for more efficient handover management, reducing the amount of signalling and interruption time. Content prefetching relies upon predictions to know which locations should pre-fetch data, in order to improve performance and energy efficiency of the mobile system. Opportunistic caching for handovers in a mobile system that utilises a passive optical network backhaul relies upon predictions to efficiently use the restricted memory space available at base stations for caching to improve handovers. Future mobile technologies are shifting toward smaller cell sizes, such as Femtocells, to improve spectrum re-use and mobility predictions are necessary to decrease the amount of unnecessary handovers in these dense small cell topologies. Many location-based services, such as shared ride recommendations or targeted ads, are also heavily dependant upon predictions to provide a good quality of service.

A wide range of approaches for providing mobility predictions, including Markov-based, Compression-based , Mixture model-based, Trajectory-based and many others have been proposed, all with the singular aim of providing a predicted future location or locations, either in the short term or the long term, for a given mobile user. However, this format of predictions is too restrictive. By providing predictions of only the most likely future location for a user, we are depriving services of a great deal of useful information that could positively influence their behaviour. If instead, services had full knowledge of the probabilities of moving to each possible future location, they could make more informed decisions and provide a more efficient utilisation of resources.

This paper mainly focuses on predicting the future locations of a vehicle using the mathematical model markov chain.

3. RELATED WORK

In[1], according to the background of related technologies of UAV, a mobility prediction clustering algorithm (MPCA) relying on the attributes of UAV was proposed. The dictionary Trie structure prediction algorithm and link expiration time mobility model are applied in this clustering algorithm to solve the difficulty of high mobility of UAV. The simulation shows that the reasonable cluster-head electing algorithm and on-demand cluster maintenance mechanism guarantee the stability of the cluster structure and the performance of the network.

With the increase of node mobility, the performance of MPCA algorithm is better than that of other algorithms. This is due to use a more reliable mobility prediction model and the Trie-based structure prediction algorithm, thus ensuring a more stable cluster structure. The simulation experiments showed that the algorithm has a certain rationality and stability and improves the network performance provided the cluster head is re-established in low cost.

The main drawback in this proposal was maintaining the cluster head. If the cluster nodes leave the clusters the structure of the cluster changes and it becomes time consuming job to update the cluster head.

LIMITATION:

- The cluster head re-establishment is a time consuming job.
- Prediction accuracy varies if the cluster nodes changes its structure.

In [2],a Markov-based prediction model which focuses on new mobile users behaviour prediction was proposed. In order to assess this approach, they used data sets of a real cellular network in a major US urban area. The efficiency of the prediction model relies on both the ability of the model to predict successfully the next move of a mobile user and its ability to perform such a prediction in a short delay. Comparing this approach with previous solutions, the have showed that their solution outperforms in all cases the previous solutions and essentially succeeds to make better predictions for new mobile users.

They have developed a mobility prediction approach which takes the advantage of the two-nodes network architecture. This approach was based on two complementary algorithms: a Global Prediction Algorithm (GPA) and a Local Prediction Algorithm (LPA). While the former was implemented at the enhanced gateway level and detects the regular movements of the mobile users using the mobility trace and a second order Markov chain, the latter was used by the base station and tracks more closely, within the cell, the movements of the mobile users. This approach consists first in calling the Global Prediction Algorithm (GPA). If this one fails in providing a (correct) prediction because of unexpected directions taken by the mobile, the prediction is yield to the Local Prediction Algorithm (LPA). If both GPA and LPA fail to provide a prediction, a multicast is performed by the EGW.

LIMITATIONS:

- Computationally not extensive

Variations in propagation, Fluctuations in the network coverage area

In[3], mobility prediction technique via Markov Chains with an input of user's mobile data traces to predict the user's movement in wireless network was proposed. The main advantage of this method was that the prediction will give knowledge of user's movement in advance even in fast moving vehicle. Furthermore, the information from prediction result can be used to assist handover procedure by reserve resource allocation in advance in vehicular network. This algorithm was simple and could be computed within short time; thus the implementation of this technique gave the significant impact especially on higher speed vehicle. Finally, an experiment was performed using real mobile user data traces as input for Markov chain to predict next user movement. To evaluate the effectiveness of the proposed method, MATLAB simulations are carried out with several users under same location zone. The results showed that the proposed method predicts have good performance which is 30% of mobile users achieved 100% of prediction accuracy.

LIMITATIONS:

If the data trace of the mobility is low then the accuracy in the predictions of the future locations is low.

In[4], an algorithm that determines the type of road, using the data available from existing hardware, on which the vehicle is being driven – city, rural, highway, or suburban – and the type of driver – aggressive, economical, or normal – was developed at Schaeffler. The algorithm also determined and constantly updated the real world duty cycles for different parts of the world. This helped in development and validation of systems for their actual usage. This algorithm took vehicle data such as wheel speed, throttle position, and brake switch status as inputs. Using those signals, the algorithm calculated several parameters such as acceleration, mean speed, throttle variations, shifts per specified interval etc. Using those parameters, the algorithm tried to identify the type of road on which the vehicle is being driven by comparing against the reference values for each parameter for every road-type. In addition, it reads driver inputs such as accelerator pedal, brake pedal and gear shift patterns to identify the driver type. A decision block is deciding the final road-type by considering decisions from driver type and road type determination. For each identified road-type, the algorithm logs the parameters of interest, which are uploaded to a cloud server. Only the final calculated parameters are uploaded instead of the time-based data array to avoid heavy data traffic. The server receives those parameters from several similar vehicles and determines a new set of parameters for a given geographical area. After rationality checks, the parameters are then updated on the vehicle. The only requisite is that the vehicle must be continuously connected to the Schaeffer cloud through internet. The algorithm has been verified with an ROC value of about 85 % for road-type determination.

LIMITATIONS:

- Connectivity to the internet for the Schaefller cloud is needed which cannot be met all the time.

In[5], the issue of predicting the next location of an individual based on the observations of his mobility behaviour over-some period of time and the recent locations that he has visited was addressed. This work had several potential applications such as the evaluation of geo-privacy mechanisms, the development of location-based services anticipating the next movement of a user and the design of location-aware proactive resource migration. In a nutshell, they extended a mobility model called Mobility Markov Chain (MMC) in order to incorporate the n previous visited locations and they have developed a novel algorithm for next location prediction based on this mobility model that they coined as n-MMC.

Human mobility is modelled by four different location predictors. The experiment resulted in the conclusion that the more complex predictors are not necessarily much more accurate than the Markov predictors. They also established that Markov predictors beyond the second order(i.e., basing their predictions on the $n \geq 3$ previous locations) are less precise. The input to this proposed algorithms was both the Transistion matrix and previously visited locations. To summarize, the results, the algorithm consistently showed that the accuracy and predictability are optimal (or almost optimal) when $n = 2$, with an accuracy and predictability ranging from 70% to 95%.

LIMITATIONS:

- The accuracy can be high as far as the current and the previous locations are available.

Input data needs more storage capacity than the processing capacity

In[6], system for passively tracking a target vehicle whose driver is assumed to be a "person of interest was presented." The tracking system relies on the dynamic recruitment of neighbouring vehicles of the target as agents. A mobility prediction algorithm is used to probabilistically predict the target's future movement and to adjust the tracking process. Combining agent-based tracking and mobility prediction enables a target vehicle to be passively localized and tracked in an efficient manner.

The authors demonstrated that most localization techniques suffer from inherent inaccuracies that may not be acceptable for vehicular-based applications that require precise location information. In such situations, the best solution is to use data fusion where the results of multiple localization techniques are combined to increase accuracy while localization techniques for vehicular networks are usually GPS based, not all vehicles are equipped with GPS devices. Also, GPS-based techniques are useless when GPS signals are not available. A popular tracking technique that is well suited to vehicular scenarios involves map-matching tracking, which attempts to match a node's actual location (raw) data to maps. It is difficult to predict for the real time tracking using these techniques.

Vehicular mobility prediction algorithm that probabilistically predicted the near-future movement of the target vehicle based on its current location and estimated speed, assuming that the target has already been localized was proposed. The algorithm incorporates: (i) time prediction, which estimates the time elapsed before the target reaches the next intersection; and (ii) direction prediction, which identifies the direction that the target will most likely take after passing the intersection.

Predicting the time taken for a vehicle to reach the next intersection requires an estimate of the speed of the vehicle. Predicting the direction that a target vehicle will take through the next intersection is more complex and bears a probabilistic distribution. Also, it presupposes that the target vehicle has been accurately localized in order to identify the lane it occupies. We assume that all drivers adhere to the following basic traffic rules.

LIMITATIONS:

- Prediction of the time is based upon the assumption that the distance between the vehicles is horizontally aligned which may not be true in all scenarios.
- Direction prediction fails if the assumption of obeying the rules is violated.

In[7],A Driving Intention Prediction Method Based on Hidden Markov Model for Autonomous Driving, driving intention prediction method based on Hidden Markov Model (HMM) was proposed for autonomous vehicles. HMMs representing different driving intentions are trained and tested with field collected data from a flyover. When training the models, either discrete or continuous characterization of the mobility features of vehicles is applied. Experimental results showed that the HMMs trained with the continuous characterization of mobility features gave a higher prediction accuracy when they are used for predicting driving intentions. Moreover, when the surrounding traffic of the vehicle is taken into account, the performances of the proposed prediction method are further improved.

A driving intention prediction method is proposed based on HMM, which can be used to predict the future moving intention of a given targeted vehicle, when a trail of mobility features is available. For the targeted vehicle, a historical trail of its mobility features is used to predict its driving intention. The lane change or lane keep behaviour is predicted based on the users driving intension history.

Adding the trails of mobility features of some surrounding vehicles may significantly increase the number of features in the training of HMMs. With a limited maximum number of iterations, the training algorithms may not be well converged in the case of a large mobility feature matrix. As a result, the prediction accuracy may be dropped in some experiments where the algorithms are not well converged.

LIMITATONS:

- Including the surrounding vehicle data history of the targeted vehicle dropped the prediction accuracy.

4. PROPOSED WORK:

The proposed system is a hybrid markov model which adaptively selects the first and the second order markov model based on the quality and the availability of the vehicle data trace to predict the future location of the targeted vehicle.

4.1 VEHICLE MOBILITY PREDICTION

The section presents the proposed vehicle mobility prediction algorithm. The approach is based on a hybrid Markov chain model, which adaptively selects from the first- order or the second-order Markov chain, depending on the availability and quality of vehicle' traces. The proposed hybrid Markov model benefits from both the first-order Markov chain and the second-order Markov chain. The rationale behind using a hybrid model is that the standard first-order Markov chain models are memory- less predictors, which means that the next location (vehicle's connected RSU) depends on (*i*) it's current location,(*ii*) the current time, and (*iii*) the day of the week of the movement. The second order Markov chain model is slightly different, as the prediction considers not only the current connected RSU information, but also the one from the previous RSU connection. The utilization of two state information could increase prediction accuracy. However, when trace data includes discrete gaps, the 2-order state transition conditions will not be met, which will lead to poor performance for the second-order predictor. Therefore, in our model, the first-order Markov chain model will be applied, if the relevant OBU has only the current connected RSU information. The second-order Markov model is applied, if the OBU has the information of both the current and previously connected RSUs. a Markov chain state S_i consists of the connected RSU ID, the time stamp and the weekday of this connection. Fig 4.2 shows the parameters used in the prediction algorithms. As from the state table below, state S_{i+1} depends on state S_i only, if $S_{i-1} = 0$; while it depends on S_i and S_{i-1}, if S_i and S_{i-1} are both available. The conditional distribution of the first-order Markov chain only depends on the current location (RSU) of the vehicle, time and the week day.

4.1.1 NUMPY LIBRARY:

The predefined data is trained and to create the transition matrix. This library is used for numerical and transitional calculations on array. The Transistion probability matrix is constructed using this library. The Transistion probability matrix consists of four rows and columns determining the probability values of Transistion from one state to the other state. The sum of every rows and columns equalizes to the value 1 proving the accuracy of the probability values.
The transition probability matrix value for 4 vehicles is

```
[[0.3, 0.4, 0.2, 0.1],
[0.1, 0.3, 0.2, 0.4],
[0.2, 0.3, 0.2, 0.3],
[0.2, 0.3, 0.4, 0.1]]
```

The logic behind to calculate the next state using the markov chain transition probability matrix is

```
mobility_chain= Markov Chain(transition_matrix=transition_matrix,states=['A', 'B', 'C','D'])
mobility_chain.next_state(current_state='A')
```

International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 07 Issue: 05 | May 2020 www.irjet.net p-ISSN: 2395-0072

4.1.2 STATE TRANSISTION DIAGRAM

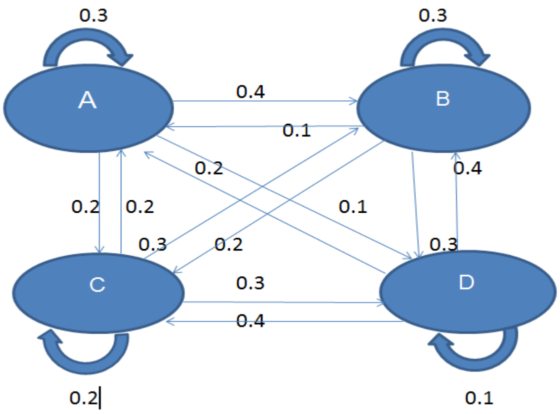
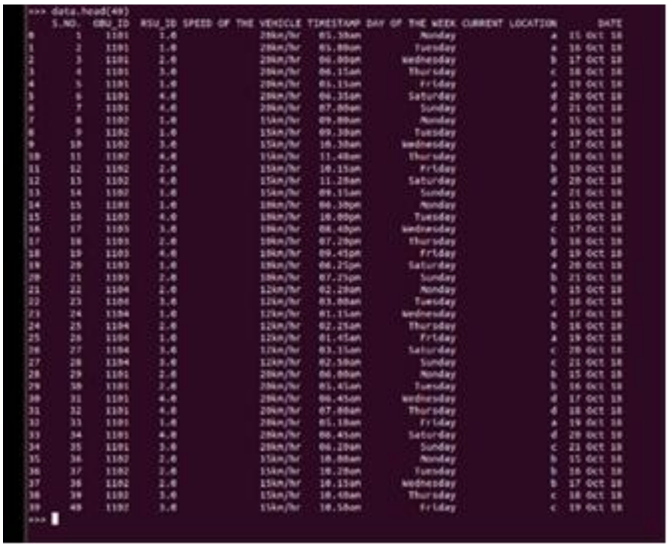


Fig -1: State transistion

4.1.3 PANDAS:

This library in python is used for data manipulation and visualization. This is used to convert excel into table containing rows and columns. This library is used to process the excel sheet by loading it and then creating the data framework. It is mainly used for the table mapping convenient for programming. The mathematical calculations needed for the mobility prediction algorithm like mean, median and for the calculations needed in the construction of the transition matrix is done through this library.



```
>>> data.head(40)
```

	S.NO.	OBU_ID	RSU_ID	SPEED OF THE VEHICLE	TIMESTAMP	DAY OF THE WEEK	CURRENT LOCATION	DATE
0	1	1101	1.0	20km/hr	01.30am	Monday	a	15 Oct 18
1	2	1101	1.0	20km/hr	01.00am	Tuesday	a	16 Oct 18
2	3	1101	2.0	20km/hr	06.00pm	Wednesday	b	17 Oct 18
3	4	1101	3.0	20km/hr	06.15am	Thursday	c	18 Oct 18
4	5	1101	1.0	20km/hr	01.15am	Friday	a	19 Oct 18
5	6	1101	4.0	20km/hr	06.35am	Saturday	d	20 Oct 18
6	7	1101	4.0	20km/hr	07.00am	Sunday	d	21 Oct 18
7	8	1102	1.0	15km/hr	09.00am	Monday	a	15 Oct 18
8	9	1102	1.0	15km/hr	09.30am	Tuesday	a	16 Oct 18
9	10	1102	3.0	15km/hr	10.30am	Wednesday	c	17 Oct 18
10	11	1102	4.0	15km/hr	11.40am	Thursday	d	18 Oct 18
11	12	1102	2.0	15km/hr	10.15am	Friday	b	19 Oct 18
12	13	1102	4.0	15km/hr	11.20am	Saturday	d	20 Oct 18
13	14	1102	1.0	15km/hr	09.15am	Sunday	a	21 Oct 18
14	15	1103	1.0	10km/hr	08.30pm	Monday	a	15 Oct 18
15	16	1103	4.0	10km/hr	10.00pm	Tuesday	d	16 Oct 18
16	17	1103	3.0	10km/hr	08.40pm	Wednesday	c	17 Oct 18
17	18	1103	2.0	10km/hr	07.20pm	Thursday	b	18 Oct 18
18	19	1103	4.0	10km/hr	09.45pm	Friday	d	19 Oct 18
19	20	1103	1.0	10km/hr	06.25pm	Saturday	a	20 Oct 18
20	21	1103	2.0	10km/hr	07.25pm	Sunday	b	21 Oct 18
21	22	1104	2.0	12km/hr	02.20am	Monday	b	15 Oct 18
22	23	1104	3.0	12km/hr	03.00am	Tuesday	c	16 Oct 18
23	24	1104	1.0	12km/hr	01.15am	Wednesday	a	17 Oct 18
24	25	1104	2.0	12km/hr	02.25am	Thursday	b	18 Oct 18
25	26	1104	1.0	12km/hr	01.45am	Friday	a	19 Oct 18
26	27	1104	3.0	12km/hr	03.15am	Saturday	c	20 Oct 18
27	28	1104	3.0	12km/hr	02.30am	Sunday	c	21 Oct 18
28	29	1101	2.0	20km/hr	06.00am	Monday	b	15 Oct 18
29	30	1101	2.0	20km/hr	05.45am	Tuesday	b	16 Oct 18
30	31	1101	4.0	20km/hr	06.45am	Wednesday	d	17 Oct 18
31	32	1101	4.0	20km/hr	07.00am	Thursday	d	18 Oct 18
32	33	1101	1.0	20km/hr	05.10am	Friday	a	19 Oct 18
33	34	1101	4.0	20km/hr	06.45am	Saturday	d	20 Oct 18
34	35	1101	3.0	20km/hr	06.20am	Sunday	c	21 Oct 18
35	36	1102	2.0	15km/hr	10.00am	Monday	b	15 Oct 18
36	37	1102	2.0	15km/hr	10.20am	Tuesday	b	16 Oct 18
37	38	1102	2.0	15km/hr	10.15am	Wednesday	b	17 Oct 18
38	39	1102	3.0	15km/hr	10.40am	Thursday	c	18 Oct 18
39	40	1102	3.0	15km/hr	10.50am	Friday	c	19 Oct 18

```
>>>
```

Fig -2: Transistion matrix

4.1.4 Scikit-learn

Scikit-learn is probably the most useful library for machine **learning** in Python. This library contains a lot of efficient tools for machine **learning** and statistical modelling including classification, regression, clustering and dimensionality reduction. It also supports **Python** numerical and scientific libraries like NumPy and SciPy. The dataset is passed and the training is done to predict the future location of the vehicle.

```
>>> mat.head(25)
                     S.NO.
OBU_ID RSU_ID
1101   1.0        10.250000
       2.0        20.666667
       3.0        19.500000
       4.0        22.000000
1102   1.0        10.333333
       2.0        34.333333
       3.0        29.666667
       4.0        12.000000
1103   1.0        17.500000
       2.0        19.500000
       3.0        17.000000
       4.0        17.500000
1104   1.0        25.000000
       2.0        23.500000
       3.0        26.000000
>>> accuracy_score(y_true, y_pred)
0.75
>>> 
```

Fig-3 Prediction score

5. CONCLUSION

In this project ,we predicted the next location of the vehicle by using the hybrid markov model. The future location of the targeted vehicle is predicted given the current and the past vehicle information like speed, location, RSUid, timestamp. The use of two state information increased the prediction accuracy.

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