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MOBILITY PREDICTION METHOD FOR VEHICULAR NETWORK USING MARKOV CHAIN

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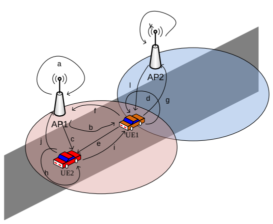
Graphical abstract



Abstract

This paper proposes mobility prediction technique via Markov Chains with an input of user's mobile data traces to predict the user's movement in wireless network. The main advantage of this method is prediction will give knowledge of user's movement in advance even in fast moving vehicle. Furthermore, the information from prediction result will be use to assist handover procedure by reserve resource allocation in advance in vehicular network. This algorithm is simple and can be computed within short time; thus the implementation of this technique will give the significant impact especially on higher speed vehicle. Finally, an experiment is 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 show that the proposed method predicts have good performance which is 30% of mobile users achieved 100% of prediction accuracy.

Keywords: Markov Chain, mobility prediction, real data traces, vehicular network

1.0 INTRODUCTION

Nowadays car and other private vehicles are used daily by many people. Citizens spend most of their time in vehicles after home and office. Every year the total of vehicles on the road always increase. According to the Automotive Demand research report of Nielsen Global Survey found out that 30% of Malaysian spent hours drove to work, while 23% of them would spent more than an hour took the train to work. Only 13% of Malaysian took over an hour to ride the bus and 18% went to work by walk [1]. Indeed, mobile communication puts forward much higher demand from consumer. Some of them are willing to pay more for seamless connectivity service while on the road [2].

Due to the emergence of mobile communication, internet connectivity is required at any places, by using any devices. In addition, the emergence of new application such as multimedia online gaming, social media and high growth of mobile devices such as laptop, tablet and mobile phone present a significant challenge. The demand of seamless internet connectivity drive attempts to provide broadband mobile wireless communication even in a fast moving vehicle. Intelligent Transportation System (ITS) and vehicular network are expected to develop to achieve traffic safety environment. The important aspect to focus on is an efficient wireless intra- and inter-vehicle communication that used to exchange data among vehicle, driver and infrastructure.

To satisfy the need for large wireless communication society, fifth-generation (5G) communication systems have emerged to give unlimited access of information and sharing the available data anywhere, any time and for any devices. 5G is expected to achieve 1000 times system capacity, 10 times spectral efficiency, enhanced energy efficiency and data rate and 25 times data throughput [3]. Hence, 5G is not about replacing with new technologies, but to enhance current technologies with new Radio-Access Technologies (RAT) in some cases and scenario [4], [5]. One of the solutions to overcome the growth of connected wireless mobile devices is deployment of small cells in dense heterogeneity network. [6].

The low-latency reliable communication between end users are difficult to achieve due to the nature of mobility. To ensure the system reliability and real time performance is achieved, underlying technologies that determined by handover performance must be considered in the first place. In order to provide Quality of Service (QoS) for high speed users, the handover is a main element that should be challenged in wireless cellular network [7]. The deployment of base stations (BS) increase rapidly in 5G small cell network particularly in the urban areas challenges handover management among vehicles especially for high speed velocity vehicles [8]. Further, high speed mobile user only have limited time spend to pass through overlapping region in small cell size. When the minimum handover process time is larger than time interval for high speed mobile user passing through overlapping region, handover process fails to complete and resulting call drop. A ping-pong effect may also happen when a call is handover to a new base station and handed back to the source base station in less than a critical time [9].

In this paper, mobility prediction that utilizes Markov Chains with assistance of user's mobility data traces is proposed. The paper is organized as follows: Section 2 describes related work on mobility prediction in wireless network. Section 3 presents an approach of the network model scenario. Section 4 presents proposed mobility prediction via Markov Chains with input of user mobility data traces. Section 5 discusses an experimental evaluation and analysis of the experiments. Finally, a conclusion is presented in Section 6.

2.0 RELATED WORK

Many studies have shown that, people often using similar routes and the routes are highly predictable [10]–[13]. Mobility prediction is known as an effective technique to optimize handover performance by performing resource allocation in advance and reduce the unnecessary handover. It trace the user history mobility and compute mobility prediction based on user mobility traces. A number of studies have been done to investigate and enhance the mobility prediction technique in wireless networks. Various techniques in mobility prediction have been proposed such as mobility prediction based on user mobility history information, prediction based on Markov chain, prediction based on user's location and signal strength.

2.1 Prediction based on User's Mobility History

Most of the existing work in mobility prediction is based on user's mobility history. This technique required traces of user movement to pre-provision network resources. The network will search the route of user and predict a set of potential handover based on user history and current location. However, this technique is applicable to the users who are frequently using the same route. Further, it is expected that drivers use consistent driving habits such as same lane and speed. For instance, the author in [10] use historical information contains all WiFi information with GPS tracked and timestamps to develop a unique approach for predictive methods. The work in [14] use Kalman Filter to predict future vehicle's location from real traffic vehicles traces that collected from VANET under different situation and location. The authors in [15] proposed prediction model based on people movement by monitoring the movement history for every mobile user through mobile telecom service. The objective of the work in [16] is to predict user's displacement based on mobile user's behavior by ant colony called ant colony optimization (ACO).

2.2 Prediction based on Markov Model

Markov Chain is a type of predictors that represent mobility behavior. It predicts the next location based on previous or current location.. The main parameter in Markov Model is a transition probability matrix. The value of the transition probability matrix is either based on assumption or train by various techniques. In [11], the authors using user's mobility history that provide frequent location and time they spend on certain places and the time is taken as an input to the transition probability matrix. Then, the transition probability matrix is used in Markov Chain equation to predict the user movement. Position-based path prediction technique are used in [17]. The suitable handover strategies are applied after the user movement has been predicted by using Markov Chain. Its only needs several movements to predict the form of the user's movement, whether it is linear, random, and patterned etcetera. The authors in [18] propose a two-stage Markov process based mobility prediction algorithm for predicting the future location of taxis. In [13], destinations are predicted based on the source of the vehicle. The vehicular mobility pattern is extracted first by using Variable-order Markov models from real data traces that collected before.

3.0 MODEL

The overview of envisions about the vehicles network data available and the system network architecture is explained first before describe about prediction have open access mode.. Every node or Access

Point (AP) record its coordinates as well as its number. Besides, there is centralized approach to collect history of every node and execute prediction algorithm. Therefore, the trajectory of the vehicles is denoted by sequences of AP numbers, which form a model for prediction scheming.

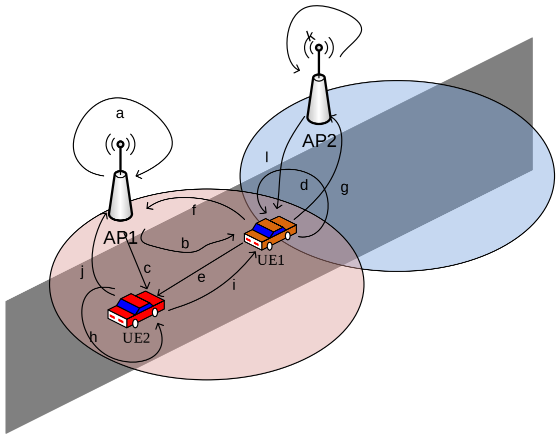


Figure 1 Vehicular communication network considered scenario

4.0 PROPOSED TECHNIQUE

As has been mentioned before, the mobility prediction can enhance the handover performance by reducing handover latency, packet jitter and end-to-end delay. One key approach for mobility prediction is by using Markov Chain predictor. This section will explain about proposed mobility prediction that uses Markov Chain as a technique to assist handover procedure in vehicular network. Markov Chains is a mathematical system that undergoes transitions from one state to another. It is a random process usually characterized as memory-less; which is the next state depends only on the current state and not on any previous states [19]. Markov Chains is a transition system composed of:

1. A set of state $S = \{s_1, \dots, s_n\}$; in which each state corresponds state vector of vehicle
2. A set of transitions n; in which each transition represents a movement from the state.

The entire movement process for a vehicle is recorded using the mobility pattern matrix in $M \times M$, where M denotes the total number of cells that make up the area in which the vehicle moves. Therefore the transition probability matrix P is written as:

$$P = \begin{bmatrix} p_{11} & \cdots & p_{1m} \\ \vdots & \ddots & \vdots \\ p_{m1} & \cdots & p_{mm} \end{bmatrix} \quad (1)$$

In this research, Markov Chain predictor is considered to predict the destination of the vehicles. The predictor uses transition probability matrix derived from a diagram called state Markov Chains diagram. The values of transition probability matrix P are derived from a diagram called Markov Chains state diagram.

Figure **2** shows how transition probability matrix P is developed from Markov Chain state diagram. Consider A and B is two states or two base stations. Every row represents a serving base station, while column represents a target base station. In this scenario, user will have two probabilities in each base station, for instance user moves from state A to state A and from state A to state B, respectively. The total probabilities for each row must equal to 1. From the transition probability matrix P, the most frequent base station that the users visit can be detected easily [20].

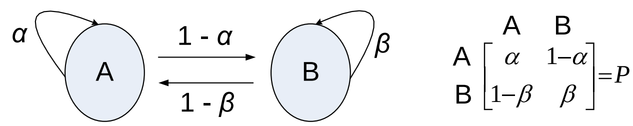


Figure 2 Markov Chain State Diagram and Transition Probability Matrix

Beside the transition probability matrix P, another parameter need to be considered is initial distribution matrix p. The value of initial distribution matrix can be derived from vehicle's velocity, distance, direction or initial state. In this paper, we focus on location and velocity as value of the initial distribution matrix. The initial state vector of proposed prediction algorithm consists of vehicle's location and speed. Therefore, let $p_t = (x_t, v_{xt}, y_t, v_{yt})$ be a 4×1 state vector, where x_t and y_t represent coordinates location of the vehicles. While, v_{xt} and v_{yt} represent speed of the vehicle along the x- axis and y- axis. Then, v_{xt} and v_{yt} represent average speed within Δt, because state vector assumed not significantly change [14]. Therefore, the new coordinate in the next step can be estimated by:

$$\begin{aligned} x_t &= x_{t-\Delta t} + v_{xt}\Delta t \\ y_t &= y_{t-\Delta t} + v_{yt}\Delta t \end{aligned} \quad (2)$$

Therefore the position of vehicle after n movement, p_n can be derived as:

$$p_n = p_t[P]^n \quad (3)$$

where,
p_t = Initial distribution,
P = Transition probability matrix,
n = Number of state transition.

4.1 User's Mobility Data traces

The collection of user's mobile history provides useful information such as frequent visited locations, common routes and received radio signal [18], [21-22]. However it is not easy to deal with such data. The user's mobility history may consume much memory, energy and bandwidth, especially at the base station that frequently visited. Therefore, the data has to be checked and pre-processed before do analysis. A method called data mining is needed to extract and analyze data.

First step in data mining process is to create log report. The format of log report is inspired by [21]. Data contain in log file are date, location, time and transport. Date represent a date the user connect to base station. Location represents base station ID the user connects at a particular time. Time represent time user connected to the particular base station. And lastly, transport represents what kind of transport they are used at particular time, because different vehicle give different speed. This log file is updated each time user move from one location to another. Data collection is done by considering some assumption:

1. Wireless network in campus is accessible.
2. All APs are located in every building.

Data collection must be done when mobile client is in idle mode and not communicating with any AP. The idle mode is chosen to avoid effect on actual data performance. In this research, a group of real vehicles user mobility traces in UTM, JB campus is use which are undergraduate students, post-graduate students and staff. From the pre-process original data, the mobility trace denotes that associated history of each vehicle by the cell number in the network under a simple mobility model assumption. The key aspect of this work is to develop an algorithm that exploit user's historical data about mobility for design handover prediction scheme.

After logging report is acquired, transactional database is created to relate between source and destination base station. Most frequent visited base station will be detected via the database.

Figure **3** shows the step of transactional database development. First, logging report is converted into source-destination table to identify user's trajectory. From source-destination table, transactional database is developed base on the relationship between source and destination AP. First column at transactional database represents source AP and first row represents destination AP. The value of each relationship determine by the frequency of user attached to each AP. For example, value 1 in transactional database refers to the frequency of user move from AP2 to AP3. Grand total is the total amount of user's transition from each base station to another. For instance, value 3 is the total time of user move or attach to AP2. Once the transactional database is created, the transition probability matrix is generated. Value of transition probability is verified using summation for each row that should equal to 1. Then, this transition probability matrix is used in Markov equation (3) to predict vehicle's next location.

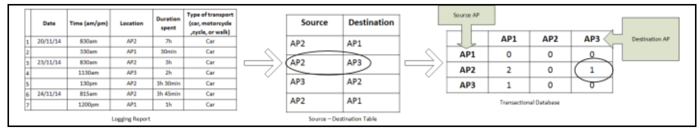


Figure 3 Step for develop transactional database

After mobility prediction is calculated, performance evaluation is important requirements for proper estimation. The prediction accuracy is a main evaluation metrics for prediction performance for mobile user's next location. Predicted result is checked to mitigate an error in prediction. Ideal case in handover is mobile user should handoff to adjacent base station. However, if predicted base station is not adjacent to previous base station, the predicted base station is considered error. We define the ratio of prediction accuracy based on ratio between numbers of correct prediction compare to total number of predictions. Flowchart of proposed mobility prediction process is shown in
Figure **4**.

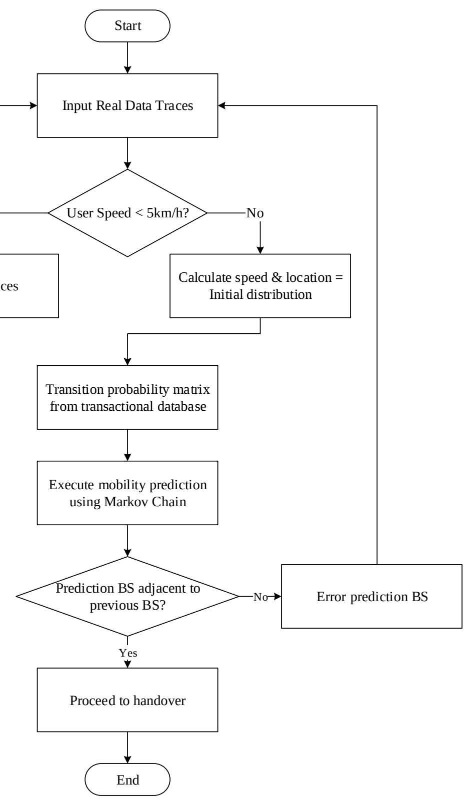


Figure 4 Proposed mobility prediction algorithm

5.0 SIMULATION AND EVALUATION

The simulation has been done in MATLAB to determine the movement of users using Markov Chain. The prediction process starts from the first location of cell until last location of cell. Then, performance evaluation is performed by calculating the prediction accuracy that defined by ratio of correct prediction to total number of predictions.

In order to simulate in realistic way, a real-life geographic features is needed to guide the possible movement directions of mobile user. In real-life, mobile user movement are restricted by the road topology. Although the destinations of moving mobile users are not the same, their movement trajectories in the same local area should follow limited number of mobility patterns, which restricted by the local geographic layout. Thus, in order to generate realistic traffic flows, local geographic details are introduced in the simulation area and used in this research.

Figure **5** shows the geographic grid elements which are used to build the simulation area and provide geographic details.

The simulation has been done to predict mobile user's next location using Markov chain with certain geographical area based on mobile user real data traces. The result has been plotted in a graph as shown in

Figure **6**. Figure 6 shows prediction of single mobile user movement. The dot in graph shows the coordinate of location for every AP that mobile user attached. The mobile user move from BS2 to BS3. Then, user moves to BS11, BS10 and BS8. After that, the user turns right at the junction and move to BS13 until BS12. The result shows that the mobile user predicted movements are same with actual movements for several time until mobile user predict last position that stop at its initial state. This is because, the predicted initial state is not same with mobile user actual initial position. It means that, this algorithm predict almost similar to actual user's position.

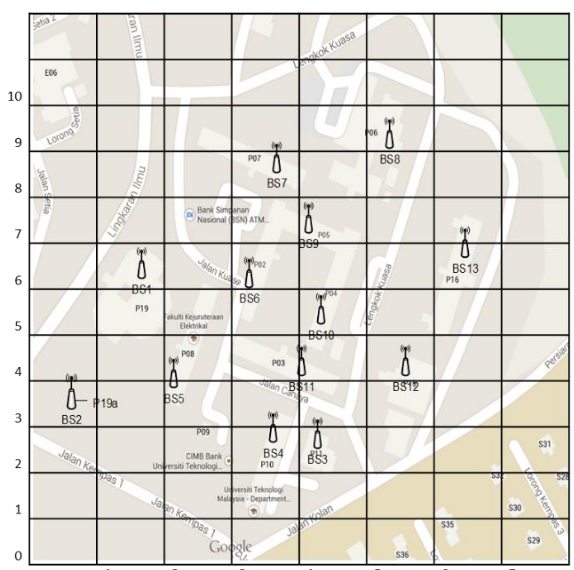


Figure 5 Geographic grid elements in the simulation area and cell number

Another simulation has been done where we evaluate the prediction performance. For prediction performance evaluation, cumulative distribution function (CDF) and histogram graph have been plotted in the

Figure **7**. From CDF plot in

Figure **7**(a) shows that 60% of mobile user achieve prediction accuracy at about 0.5. We also can see that 30% of mobile user achieves 100% of prediction accuracy. It shows that the proposed prediction algorithm give good performance and less error.

Figure **7**(b) shows the histogram of prediction accuracy by 17 of mobile users for proposed prediction algorithm.

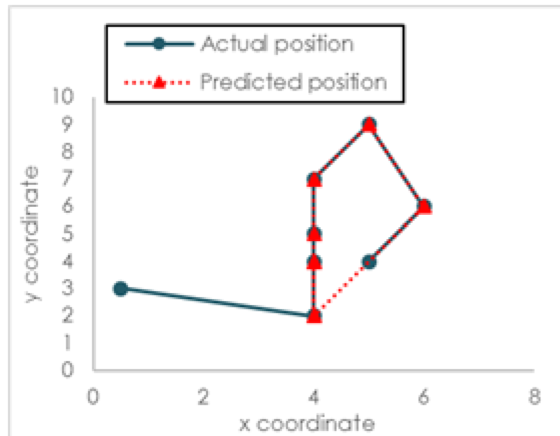


Figure 6 Prediction of single mobile user

As we can observe from the figure, the results are consistent with the CDF plot. Most of mobile users achieved 90-100% prediction accuracy. Then, the prediction accuracy is compared with other proposed method such as heuristic database in [21] which rely in user's mobility history. Based on simulation result, prediction accuracy is increased when user's mobile history is collected in longer duration. Prediction accuracy for proposed method is increased to 80% when mobile traces is collected until 5th weeks, while other technique shows decreasing prediction accuracy at same duration.

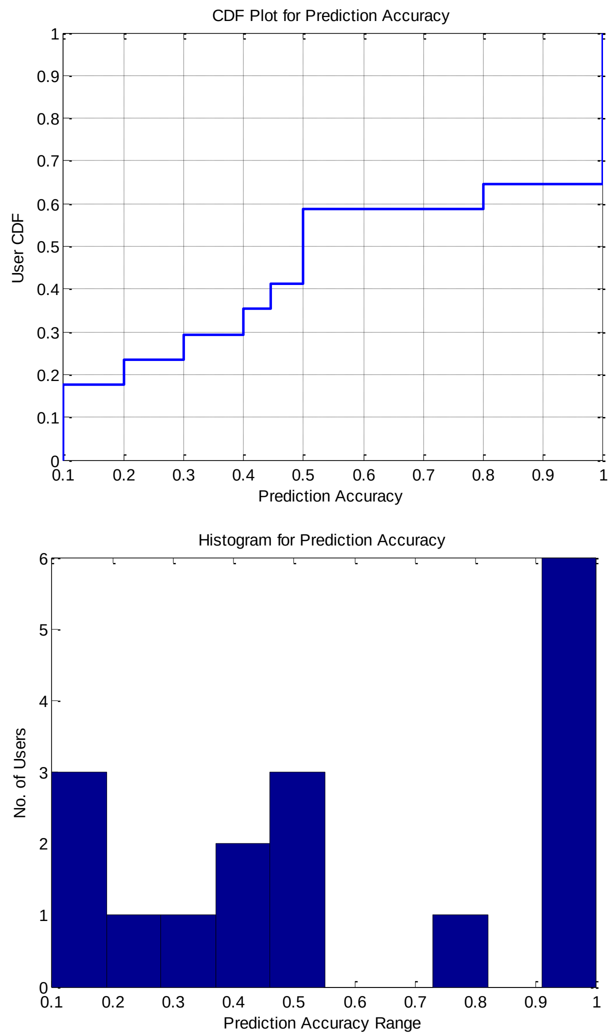


Figure 7 Prediction accuracy measured for a group of mobile users

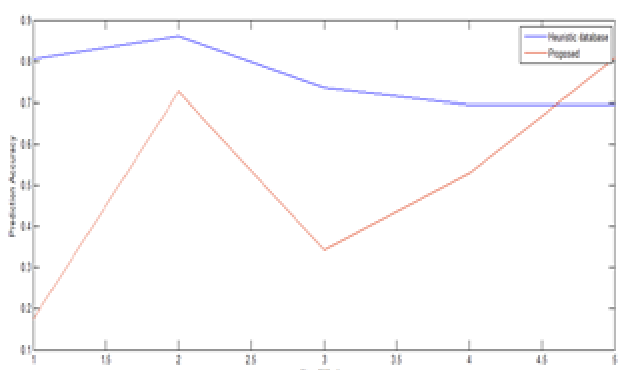


Figure 8 Prediction accuracy with varied duration of user's mobility history

6.0 CONCLUSION

In order to provide QoS for high speed user, handover is a main factor need to consider in wireless cellular network. One of the 5G goals is to support seamless and reliable performance to maintain communication in network. Mobility prediction has been proved to enhance the handover performance by allocating the resource in advance and reducing unnecessary handover. One of mobility prediction technique is by using Markov Chain.

This paper has performed mobility prediction technique for mobile user in vehicular network using Markov Chain. The result shows that the next vehicle position can be predicted with real mobile data traces as input. The results also show that about 30% of mobile users achieved 100% of prediction accuracy. It shows that the proposed mobility prediction algorithm have good performance in terms of accuracy. We compared the performance of proposed method with other method that used heuristic database. The output shows that proposed method give reliable results performance. However, the accuracy for this approach is not high for initial phase. Therefore, this approach might be improved. This proposed mobility prediction is expected to be optimized using any optimization method to achieve higher accuracy prediction and additional parameter in order to develop intelligent vehicular network.

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