MOBILITY PREDICTION FOR HIGH SPEED VEHICLE USING USER'S HISTORY DATA TRAFFIC WITH MARKOV CHAIN ALGORITHM

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ABSTRACT

This paper proposes an improved mobility prediction method using Markov Chain and real user data traffic history. The main advantage of the method is the simplicity and speed of the algorithm such that it can be computed rapidly for higher speed vehicle. The mobility prediction allows allocate the resources before user arrive at next cell. To test the effectiveness of the proposed method, MATLAB simulations are carried out under several group of user's history data. The superiority of proposed method over the heuristic mobility prediction increase about 20%. It is envisaged that the method can be very useful in the design of intelligent handover algorithm for 5G network.

1. INTRODUCTION

These days car and other private vehicles are used daily by many people. Citizens spend most of their time in vehicles after home and office. 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 (Nielsen 2014). 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 (Araniti et al. 2013). 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.

Fifth-generation (5G) communication systems have appeared to give unlimited access of information and sharing the available data anywhere, any time and for any devices to satisfy the need for large wireless communication society. 5G is expected to achieve 1000 times system capacity, 10 times spectral efficiency, enhanced energy efficiency and data rate and 25 times data throughput (C.-X. Wang et al. 2014). Hence, 5G is not about to replacing with new technologies, but to enhance current technologies with new Radio-Access Technologies (RAT) in some cases and scenario (Ericsson 2013; Kaloxylos et al. 2014). One of the solutions to overcome the growth of connected wireless mobile devices is deployment of small cells in dense heterogeneity network. (Y. Wang et al. 2014).

Due to the nature of mobility, the low-latency reliable communication between end users are difficult to achieve. 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 (Zhou & Ai 2014). 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 (Jungnickel et al. 2014). Further, high speed mobile user only has 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 handoff to a new base station and handed back to the source base station in less than a critical time (Hussein et al. 2011). Prediction method can reduce the resource allocation time.

In this paper, mobility prediction algorithm is proposed. The paper is organized as follows: Section 1 is analyzing the problem arise in high speed mobility communication network. Section 2 describes related work on mobility prediction in wireless network. Section 3 presents proposed mobility prediction via Markov Chains with input of user mobility data traces. Section 4 discusses the experiment and analysis. Finally, a conclusion is presented in Section 5.

2. RELATED WORK

Many studies have shown that, people often using similar routes and the routes are highly predictable (Deshpande et al. 2009; Amirrudin 2013; Zhu et al. 2011; Xue et al. 2012). Mobility prediction is known as an effective technique to optimize handover performance by performing resource allocation in advance and reduce the unnecessary handover. It traces 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 (Deshpande et al. 2009) use historical information contains all Wi-Fi information with GPS tracked and timestamps to develop a unique approach for predictive methods. The work in (Feng et al. 2014) 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 (Lin et al. 2013) 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 (Daoui et al. 2008) 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 (Amirrudin 2013), 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 (Ulvan et al. 2009). 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 (Chen et al. 2013) propose a two-stage Markov process based mobility prediction algorithm for predicting the future location of taxis. In (Xue et al. 2012), 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 have been collected.

3. PROPOSED TECHNIQUE

3.1 Model

The overview of envisions about the vehicles network data available and the system network architecture is explained first before describe about prediction algorithm. Wireless network for the user in vehicles that travelling from one cell to another is assumed to 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.

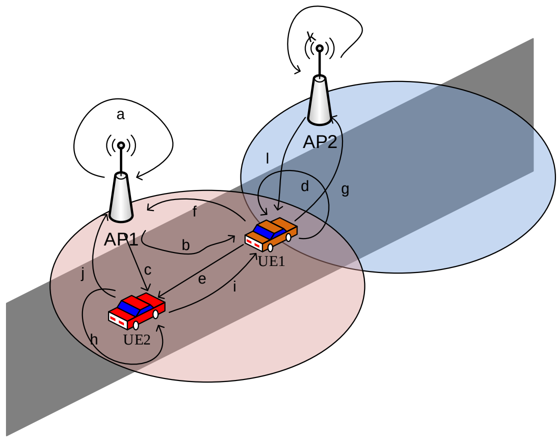

Fig. 1 Vehicular communication network considered scenario

3.2 Prediction Algorithm

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 (Gambs et al. 2012). 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:

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

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. From the transition probability matrix P, the most frequent base station that the users visit can be detected easily (Barth et al. 2011).

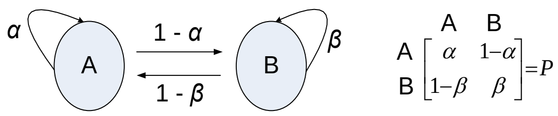

Fig. 2 Markov Chain State Diagram and Transition Probability Matrix

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

$$p_n = p_t[P]^n \quad (2)$$

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

3.3 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 (Amirrudin et al. 2013; Chen et al. 2013; Lee et al. 2014). 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. That method is called data mining process.

First step in data mining process is to create log report. The format of log report is inspired by (Amirrudin et al. 2013). This log file is updated each time user move from one location to another. Mobility traces denotes associated history of each vehicle by the cell number under mobility model assumption. 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. Once the transactional database is created, the transition probability matrix is generated. Then, transition probability matrix is used in Markov equation (2) to predict vehicle's next location. After mobility prediction is calculated, prediction accuracy is compute for proper estimation of user's next location. Predicted result will be verified to lessen any error in prediction. Flowchart of proposed mobility prediction process is shown in figure 3.

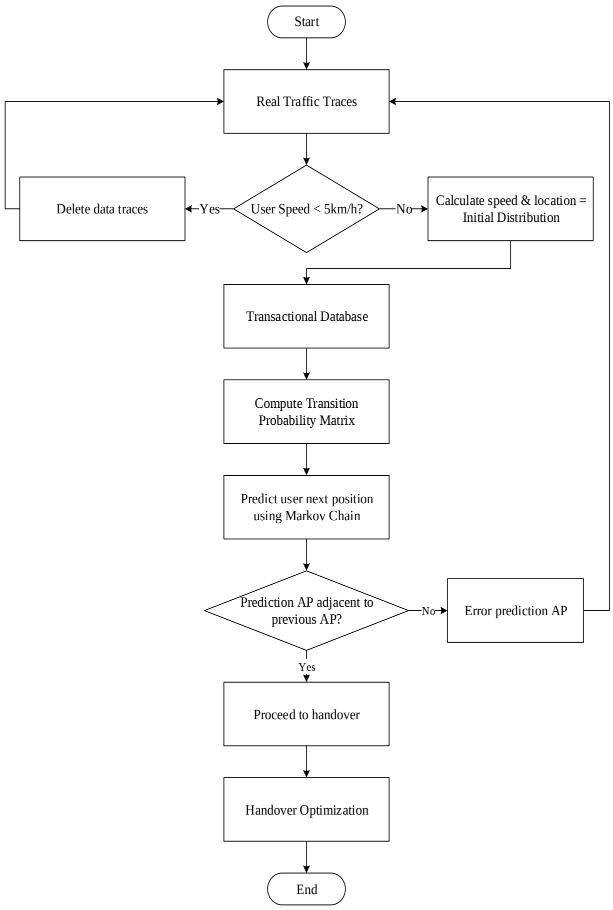

Fig. 3 Proposed mobility prediction algorithm

4. EXPERIMENT

The prediction algorithm has been implemented on a laptop using MATLAB. In order to verify the prediction algorithm, the experiments based on different set of mobility user has been performed. The three group of real vehicle mobility traces are used to evaluate the performance of mobility prediction algorithm in VANET. The real movement traces of mobile users are obtained from UTM, Johor Bahru campus which are undergraduate students, post-graduate students and staff. Although the destinations of mobile users are not same, their movements trajectories in the same local area should follow limited mobility patterns, which restricted by the local geographic area.

The result shown in figure 4 demonstrate the prediction performance for different group of mobile user. It can be seen that the undergraduate students have highest prediction accuracy compare to postgraduate and staff. This result is due to high number of undergraduate mobile users in UTM compare with other group. It shown that more mobile users can give more accurate prediction.

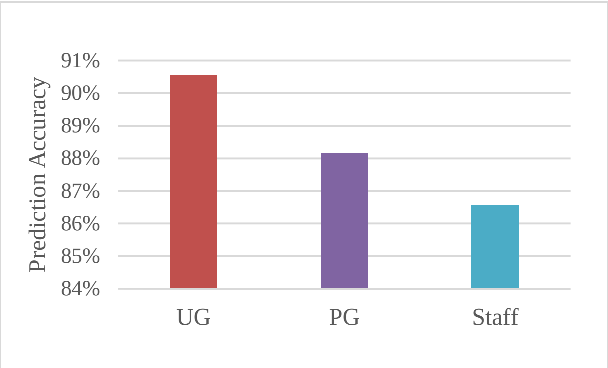

Fig. 4 Mobility prediction with different group of user

Figure 5 give performance comparisons of proposed prediction method and heuristic method (Amirrudin et al. 2013). The data shows that proposed method achieves higher accuracy prediction compared to heuristic method. The proposed method peaks at 0.92 while the heuristic method peaks at 0.71.

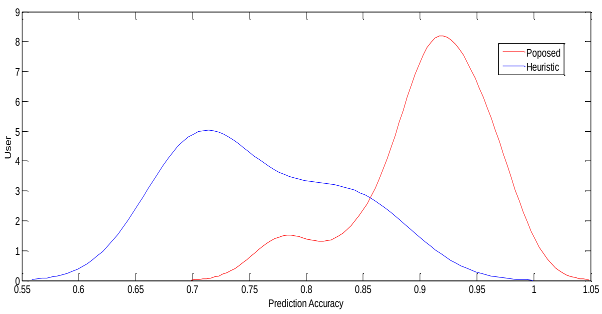

Fig. 5 Performance comparison between proposed method and heuristic method.

To summarize, the results consistently show that higher number regular user behind daily vehicles mobility contribute to higher prediction accuracy result. The prediction accuracy results in real traffic traces dataset range from 75% to 96%.

CONCLUSION

This paper discovers the possibility of vehicular network mobility prediction and the predictability of its movement pattern. The Markov chain prediction algorithm predict next cell position based on previous record movement and its history data is proposed. The prediction accuracy from the experiment ranges from 0.75 to 0.96 under 3 different groups. The output shows that proposed method give reliable result performance. In the future, this proposed mobility prediction is expected to be additional parameter in a handover algorithm in 5G network. This proposed method will be optimized using any optimization method to achieve higher accuracy prediction.

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