An LSTM-based Mobility Prediction Mechanism in the ICN-based Vehicular Networks

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***Abstract*— Conventional mobility prediction mechanisms use the global positioning system (GPS) location history of a user. However, the exiting mechanisms did not focus enough on the time-dependent sequential location history for mobility prediction. On the other hand, information-centric networking (ICN) is a recent paradigm for future Internet architecture, and the built-in caching mechanism is one of the main characteristics of ICN. In this paper, our objective is to use the sequential and time-dependent location history of mobile devices and propose an LSTM-based mobility prediction mechanism to predict the probable next position of a mobile device. Moreover, accurate mobility prediction may assist the proper handover prediction so that the caching capability of ICN can be proactively used in the ICN/cell-based vehicular network. We simulate the proposed mechanism with the real dataset, which was collected using a mobile application for six months. Our predicted simulation results ensured the correctness of the proposed mobility prediction algorithm, which leads to the end-to-end seamless content delivery by using the proactive caching mechanism of ICN and predicting the future movement direction of the mobile device.**

Keywords—Mobility prediction, vehicular networks, and ICN

I. Introduction

The ICN-based vehicular network [1] has several benefits over the current Internet-based vehicular network. The in-network caching mechanism is the most compelling characteristic of the ICN-based vehicular networks where the content can be proactively cached in all intermediate ICN nodes including mobile devices, roadside units (RSUs), and base stations (BSs). The users are connected to the ICN-based vehicular network via an RSU or BS where the requested content can be proactively cached during handover, which can ensure seamless content delivery to the users. But, the normal handover decision time is not enough for proactive caching because the content should be proactively cached to the target BS before handover. Therefore, the mobility prediction based on the user's current location and movement direction is needed for proactive caching.

The history of a user's global positioning system (GPS) [2] locations is used to track user mobility in most of mobility prediction mechanisms. The mobility of a user can also be tracked in several ways, e.g., through Sequential Monte Carlo Filtering [3], Kalman Filtering [4], and Particle Filtering [5] mechanisms. For simplicity, the well-known GPS technology is used for mobility prediction. A user's movement may change after a certain amount of time, and the changed movement can be identified by continuous user tracking. The continuously updated historical movement data can be used not to degrade the prediction accuracy sharply. The prediction model should be able to use the continuously tracked movement data in the training stage so that the accuracy can be increased in the mobility prediction mechanism.

This paper proposes a mobility prediction mechanism in ICN-based vehicular networks, and the historical data about GPS locations are used in the simulation. The rest of the paper is organized as follows. Section II describes the related work on mobility prediction, and our proposed LSTM-based mobility prediction mechanism is described in Section III. Section IV presents the performance evaluation results, and finally, Section V concludes our paper.

II. Related Work

Many positioning technologies are available to find the location of a mobile device. The GPS [2] is one of the mostly used positioning technologies among existing ones. But, the GPS positioning accuracy is not perfect in precisely locating a vehicle or autonomous car in the vehicular network [6]. To get a more accurate position of the vehicle, other mobility tracking mechanisms may be used, e.g., Sequential Monte Carlo Filtering [3], Kalman Filtering [4], and Particle Filtering [5]. On the other hand, to find the static position of any object from a map, the Spatial Conceptual Map (SCM) is a useful and essential representation of the static object. The SCM is defined as "an abstraction of a real map representing a portion of the urban environment" [7, 8].

Typically, mobility prediction depends on the user's location, and a user's location history is used in many prediction mechanisms. In some mechanisms, the current location and other related parameters, e.g., user speed and received signal strength (RSS), are still used instead of location history. An intensive analysis was done in [7] to explain the pros and cons of different mobility prediction mechanisms. The related articles predict the probable next position of the mobile devices based on the quasi-deterministic mobility behavior [9], mobile motion prediction (MMP) algorithm [10], Markov model [11], Bays model [12], fuzzy inference system [13], multilayer neural networks [14], and machine learning-based mobility prediction in SDN controller [15]. In addition, the GPS location was used [16] to predict the next location of the mobile devices. However, these mechanisms did not consider the user's sequential locations for prediction. A user's sequential locations should be used to predict a user's next location, which is impossible to be applied to several prediction mechanisms as mentioned above. Moreover, some of the algorithms above only considered the current location of the mobile device instead of the unique sequential locations, and as a result, the prediction accuracy was reduced, and therefore we consider an LSTM method [17]. Specifically, we propose a mobility prediction mechanism that can handle a series of unique sequential locations to increase the accuracy of mobility prediction.

III. An LSTM-based Mobility Prediction Mechanism

Vehicle-to-Infrastructure (V2I) communication is a higly effective way to access the remote content. Each vehicle can be connected to the Internet via an RSU or a BS. The vehicle may change the RSU or BS continuously due to its high mobility in the vehicular network, which is defined as handover in the cell-based vehicular network. The handover depends on the the level of mobility of a user. The network interface for an RSU or BS could be different, but the equipment should operate to deliver the content seamlessly in the vehicular network. For example, Figure 1 shows an ICN/cell-based vehicular network where a vehicle moves from one place to another place. The vehicle is connected to an RSU through the cellular network, and the handover may frequently happen from one RSU to another RSU if the vehicle moves in a fast manner. The content provider can provide its service seamlessly if the vehicle's end-to-end communication becomes uninterrupted.

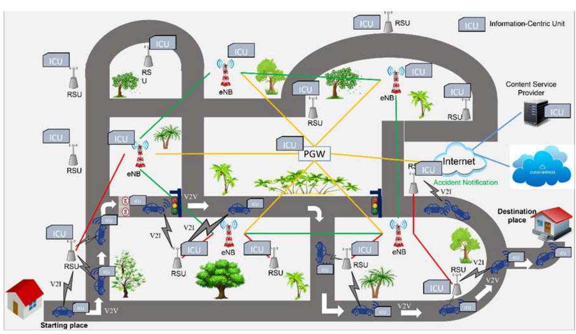

Figure 1: An ICN/cell-based vehicular network

The uninterrupted or seamless delivery is possible only if the content is delivered to the users immediately after handover. It can be realized if the content is already available on the target BS or RSU before handover by using proactive caching. The mobility prediction mechanism can assist the network in proactively caching the desired content in the next probable RSU or BS after handover. An LSTM-based mechanism is used in this paper to predict the mobility of users. The LSTM mechanism is more suitable because it can handle a series of unique sequential locations to increase the mobility prediction accuracy.

The sequential movement history is determined by the consecutive GPS locations, and the user locations are also uniquely identifiable using the consecutive GPS locations. The liner and angular distances between two consecutive GPS locations are measurable and helpful in mobility prediction. Figure 2 shows an LSTM cell. We use a well-known LSTM model in our mobility prediction mechanism.

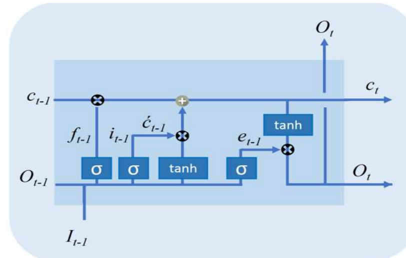

Figure 2: An LSTM cell

An LSTM cell is used to make our mobility prediction model and train and test the developed model. In Figure 2, the LSTM cell has three inputs, c_{t-1}, h_{t-1}, and $I_{t-1,}$ and two outputs, c_t and O_t. Among them, we only set the input I_{t-1}. The LSTM-based mobility prediction model only takes the input from the set of GPS locations which was collected by a cell tracker application [18] for a couple of months. It is very important to explain every state of an LSTM cell as shown in Figure 2 where the value of the forget gate, f_{t-1}, input gate, i_{t-1}, candidate state, $\acute{c}_{t-1}$, output gate, e_{t-1}, cell output, O_t, and cell memory, c_t are calculated based on the following Equations (1) to (6). Among the parameters in Equations (1) to (6), the input I_{t-1} is given, and the simulation environment handles the remaining inputs.

$$f_{t-1} = \sigma(W_f.[O_{t-1}, I_{t-1}] + b_f) \ldots\ldots\ldots..(1)$$

$$i_{t-1} = \sigma(W_i.[O_{t-1}, I_{t-1}] + b_i) \ldots\ldots\ldots...(2)$$

$$C'_{t-1} = tanh(W_c.[O_{t-1}, I_{t-1}] + b_c) \ldots\ldots(3)$$

$$c_t = f_{t-1} * \mathrm{C}_{t-1} + i_{t-1} * C'_{t-1}) \ldots\ldots\ldots\ldots(4)$$

$$e_{t-1} = \sigma(W_d.[O_{t-1}, I_{t-1}] + b_e) \ldots\ldots\ldots\ldots(5)$$

$$O_t = e_{t-1} * \tanh(\mathrm{c_t}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots.\ldots.(6)$$

Here, b_f, b_i, b_c, and b_e are the weight values of the corresponding functions, which are associated with the respective gate, layer, or state functions and assigned by the simulation environment.

IV. Performance Evaluation

We have evaluated our proposed idea in TensorFlow [19] using simulation where 80% of day-basis data from the real datasets are used to train the LSTM-based mobility prediction model, and the remaining 20% of day-basis data are used for testing purposes.

a. Mobility Prediction Result

Figure 3 shows the simulation result for real vs. predicted movement for one day among the testing day-basis dataset. The figure clearly shows that the predicted movement line is almost similar to the actual movement line and comparatively better than the existing result [7]. The real and predicted movement lines are shown in blue and yellow colors, respectively. The blue line is almost overlapped by the yellow line, indicating the correctness of a user's predicted movement.

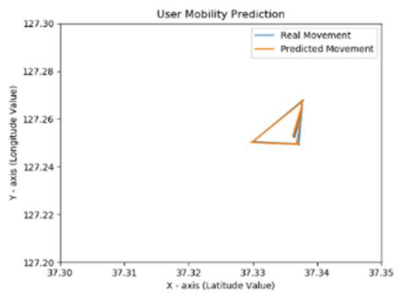

Figure 3: Real vs. predicted movement for one day

b. *Mobility prediction accuracy result*

Figure 4 shows the prediction error of the proposed mobility prediction model in a boxplot, where the prediction error is shown on the Y-axis. The minimum prediction error is 7.5%, which indicates that the maximum prediction accuracy is 92.5%. However, the average and maximum prediction errors are 10% and 15%, respectively. Therefore, the average and minimum prediction accuracy become 90% and 85%. Moreover, the outliers prediction error can be avoided because a few GPS locations may be available, which may not impact the direction of the prediction path.

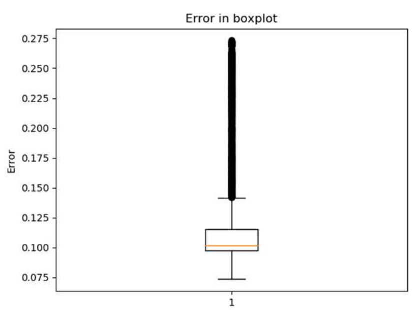

Figure 4: Prediction error in boxplot

V. CONCLUSION

This paper proposed an LSTM-based mobility prediction mechanism in ICN/cell-based vehicular networks. We used real datasets to predict the future movement of a user. The simulation results ensured the enhanced accuracy of our proposed LSTM-based mobility prediction mechanism.

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