Mobility Prediction in Wireless Networks Using Deep Learning Algorithm

Abebe Belay Adege[1](✉), Hsin-Piao Lin[2], Getaneh Berie Tarekegn[1], and Yirga Yayeh[1]

[1] Department of Electrical Engineering and Computer Science, National Taipei University of Technology, Taipei, Taiwan
abbblybelay@gmail.com

[2] Department of Electronic Engineering, National Taipei University of Technology, Taipei, Taiwan

Abstract. Recently, wireless-technologies and their users are rising due to productions of sensor-networks, mobile devices, and supporting applications. Location Based Services (LBS) such as mobility prediction is a key technology for the success of IoT. However, mobility prediction in wireless network is too challenging since the network becomes very condensed and it changes dynamically. In this paper, we propose a deep neural network based mobility prediction in wireless environment to provide an adaptive and accurate positioning system to mobile users. In the system development processes, firstly, we collect RSS values from three Unmanned Aerial Vehicle Base Stations (UAV-BSs). Secondly, we preprocess the collected data to get refine features and to avoid null records or cells. Thirdly, we exhaustively train the Long-short term memory (LSTM) network to find the optimum model for mobility prediction of the smartphone users. Finally, we test the designed model to evaluate system performances. The performance of the proposed system also compared with Multilayer Perceptron (MLP) algorithm to assess the soundness of mobility prediction model. The LSTM outperforms the MLP algorithm in different evaluating parameters.

Keywords: Long-short term memory · Location based services · Mobility prediction

1 Introduction

In Internet of things (IoT) era, where everything is connecting through internet to create smart home, smart city, smart world as well as smart society, Location Based Service (LBS) such as mobility prediction plays key roles for the success of IoT. However, developing the mobility prediction model in wireless environment is very challenging since the place and time are changed recklessly [1]. Moreover, the speed and directions of mobile users, and the dynamical oscillations of wireless network traffics are challenges in mobility prediction modeling. Mobility prediction in wireless network focuses on locating the movements of different objects, such as vehicles, animals, typhoons and tourists on a regional environments in different areas. It becomes hot issues in different

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areas, such as computer science, geographical information science and visual analytics [2]. As discussed in [3], locating users in mobile technologies can be applicable ranging from location-based services to robotics and route findings to create ranges from smart home up to smart world and society. Mobility prediction can be exploited for improving resource reservation in mobile networks. It is also uses for efficient base station deployments, efficiently planning and managing risks, properly controlling resource consumptions, safe time in certain operations and activities specifically when there will be simultaneous operations, and for improving quality of decisions.

Mobility prediction, more particularly tracking, of the movable objects are commonly predicted using satellite-based positioning such as Global Positioning System (GPS), Global Navigation Satellite System (GLONASS) and Galileo [4, 5]. Nevertheless, satellite-based applications are not well appropriate for all types geolocation applications due to the lacks of Line of Sight (LoS) and its sensitivity to occlusion [6]. The shadowing and blocks in urban areas make the usages of satellite technology inadequate accuracy. The Wi-Fi signal was proposed as additional technology to alleviate global satellite fluctuations [7], while it still has much signal fluctuation problems for outdoor environments. Moreover, Wi-Fi has coverage constraints as the Wi-Fi access points enable to cover only fewer radius. Sensor networks are other means of tracking mobile users, nevertheless it is not cost effective to apply in wider coverage.

Mobility prediction (Tracking) in mobile technology has great importance when the prediction system is more accurate and robust. It uses to aware the current and future possible destination zones of mobile users. We can apply tracking system to locate mobile carriers or users using vision based or radio signal sources of data. The vision based mobility predictions can be computed through the aid of image and video data. This approaches cause unpredictable effect when the camera or the observed objects move or cross each other. It is quite difficult to find a reliable model that works well in the different regions of the image or video, and it has accuracy defects at blurry light [8]. It has also technical difficulties, lacks of adaptabilities in wider community, security issues and the operational complexity for LBS in urban and smart city environments. Thus, radio signal based mobility prediction becomes common for offering LBS in wireless environments as it can minimize the computational complexity, applied in wider areas and cost effective for fitting IoT business models. However, wireless based data sources have much signal fluctuations due to shadowing or different network traffics to provide accurate LBS, and the problem will be more serious when the located objects are in motion. Thus, we should apply more adaptive of the wireless environment, and flexible technology according to data natures to get accurate and cost effective tracking model.

In [9], clustering was applied for location prediction using Adaptive Resonance Theory (ART), and compare with k-Means algorithms. The work was evaluated through boundary level accuracy rather than specific path. This approach is difficult to evaluate system performances. In [3], the lookup table correlation technique was used. However, this type of approach is impractical when the data size is larger and complex. In [10], the trajectory prediction has been done in the indoor environment.

According to [11, 12], there are two widely classified mobility prediction approaches: network based and handset based methods. In network based technology, the network-based position determination equipment is required to position the mobile device.

The measurement can be done from BSs and Access Points (APs). This approach is highly depending on service providers. The common approaches under this method are Angle of Arrival (AoA), Time of Arrival (ToA) and Time Difference of Arrival (TDoA). In contrast, the handset based positioning technique determines the future location of the mobile device by putting its location by cell identification, and signal strengths of the home and neighboring cells. This type of approach is determined using client software installed on the handset or in server. This technique is easy and common. It is also cost effective because it doesn't require extra devices. Tracking in wireless and mobile network requires more adaptive algorithms since there is much signal fluctuations due to shadowing or network traffic effects [9].

In this work, we propose a Long-short term memory (LSTM) algorithm as it is very powerful in capturing spatial and temporal dependencies in input and output data sequences. LSTM has also a nonlinear transformations and hidden-state memory units, that uses to predict motions accurately. We use Unmanned Aerial Vehicle Base Stations (UAV-BSs) to collect data sources from 500 m by 300 m working area, which is located in Taiwan, National Taipei University of Technology (NTUT).

The rest of this paper is organized as follows. In Sect. 2, we discuss details of the proposed technique. The data collections, results and discussions are presented in Sect. 3. Finally, conclusions and recommendations are given in Sect. 4.

2 Proposed System

Figure 1 illustrates the general flow of system architectures in both training and testing phases. Once we collect relevant datasets from UAV-BSs, we apply preprocessing to filter and make structured data based on UAV height and the received power. The system has two phases: training and testing phases. After the LSTM is trained through adjusting various parameters, such as hidden layers, epochs, activation functions and optimizers, we were training the LSTM exhaustively until we get the optimum performances. In testing phase, we collect from unknown locations in the working path, during moving instances. The predicted values are compared with real values in graphical path and mathematical computations.

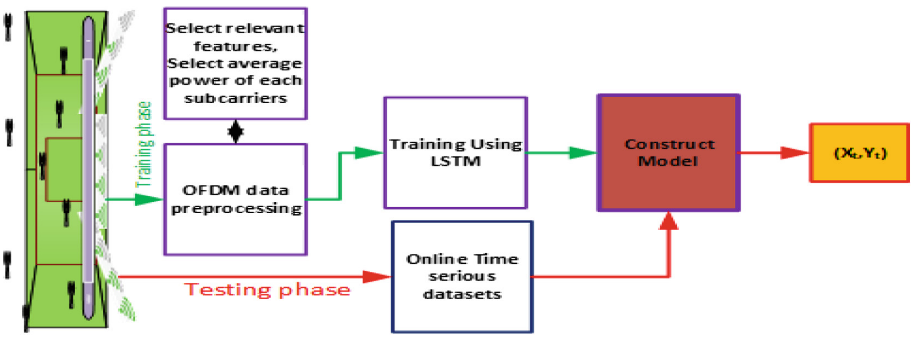

Fig. 1. Proposed algorithm pseudocode

In Fig. 2, the structure of LSTM algorithm with its gates is demonstrated. Cell A is the previous cell containing the previous stored memory C_{t-1} and previous hidden layers h_{t-1}. Each gate uses to predict the paths of the mobile users, which is determined based on the available OFDM signal. In general, LSTM network contains information or subparts such as current cell, current input unit X_t, current hidden state h_t, the current output gate O_t, the internal memory unit C_t, the input gate i_t, the forget gate f_t, and activation functions.

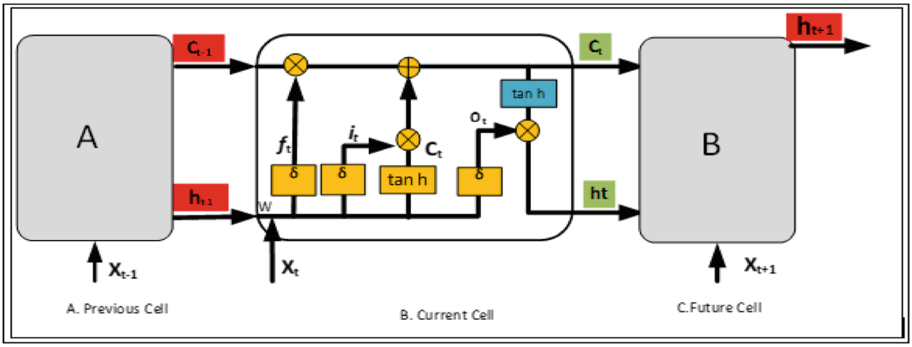

Fig. 2. The LST algorithm structural layouts

Where,

$$f_t = \delta(W_f.X_t + W_f.h_{t-1} + b_f) \tag{1}$$

$$i_t = \delta(W_i.X_t + W_i.h_{t-1} + b_i) \tag{2}$$

$$O_t = \delta(W_o.X_t + W_o.h_{t-1} + b_o) \tag{3}$$

$$C - in_t = tanh(W_c.X_t + W_c.h_{t-1} + b_{c-in}) \tag{4}$$

$$C_t = f_t.C_{t-1} + i_t.C - in_t \tag{5}$$

$$S_t = O_t.tanh(C_t) \tag{6}$$

The proposed system is evaluated by demonstrating the path direction as well as the moving object approaches. Moreover, we evaluate the system accuracy in each testing point relative to the actual places. The estimation errors are calculated by taking each estimated location in different time intervals. The errors of each mobile user at each different time intervals t $= \{1, 2, 3, \ldots.\}$ is evaluated, as shown in Eq. (7):

$$P_t^k = \sqrt{\left(X_{ol} - EL_{xt}^k\right)^2 + \left(Y_{ol} - EL_{xt}^k\right)^2} \tag{7}$$

where P_t^k is the error at time t from original location of (X_{ol}, Y_{ol}), l is the location where we measured in working environment, and EL_{xt} is the estimated locations of the user k in certain time instances. Moreover, the system performances are evaluated in mean square errors (MSE) and mean absolute errors (MAE) to show the bounded error of the system performances in each algorithm. The programing frameworks are done using Python 3.7 programming language with the Tensorflow framework.

3 Data Collection and Performance Evaluations

For this work, we collect Orthogonal Frequency Division Multiplexing (OFDM) data from defined path that covers 300 m *by* 500 m, NTUT. This data is collected from three UAV-BSs that are elevated on 40 m, 50 m and 60 m heights of buildings. The heights variations use to make the proposed system easily adapt the real scenario because most fixed BSs are deployed between 40 m to 60 m, while it can deployed in the range of 20 m to 80 m according to landscapes on outdoor environments [13]. Besides, it adapts the signal strength fluctuation through angle of elevations as the real world land scape has various up and downs. The datasets are recorded in three seconds interval, periodically, to evaluate the proposed system uniformly, and minimize performance evaluation biasedness. The collected data has the form of (I, H) ➔ (x, y), where I and H are scanned data or RSS values and the corresponding heights of the UAV-BSs, respectively. H has three different possible values: 40 m, 50 m and 60 m. In each record, we use one of the three H values. The sample signal distribution from two UAV-BSs at different heights is shown in Fig. 3.

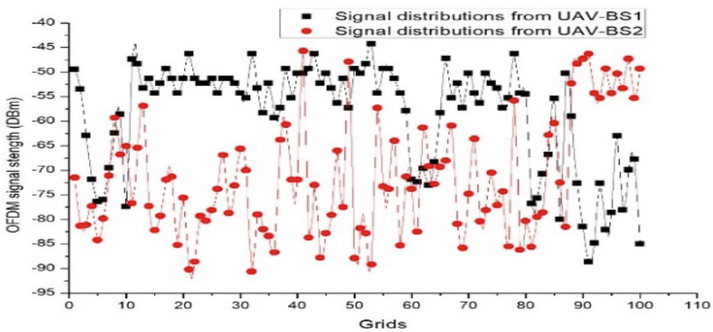

Fig. 3. Sample signals distribution from two UAV-BSs

Table 1 shows some of the parameter setups in the UAV-BSs. We fix the bandwidth to be 15 kHz to make the proposed system can adaptive the wider signal fluctuations as the narrower bandwidth has much signal fluctuations. We use universal software radio peripheral (USRP) device and software defined radio (SDR) system to generate the real signal from Ubuntu computer. We used open SDR code with little modifications, where the SDR is originally written by GNU radio companion (GRC) in C language for Ubuntu platform. We used the power amplifier to increase the signal power from transmitter, Tx, since the power of USRP in the Tx side needs much power. Besides, we used dipole antenna in both Tx and receiver, Rx, and the output power of the USRP set 24.8 dBm. In Rx side, the computer reads and stores the OFDM signals that received from Tx in each reference point. We set carrier frequency to be 860 MHz as this frequency is free from Taiwan Telecommunication services while wireless media unable to be absolutely free from signal interferences.

Table 1. Simulation parameters.

Parameters	Values
Height of the buildings	40 m, 50 m, 60 m
Center frequency	860 MHz
Bandwidth	15 kHz
Signal type	OFDM
Transmission power (T_X)	33 dBm
Receive power (R_X)	24.8 dBm

Figure 4 shows the training and validation performances of the MLP and LSTM networks in loss functions and epoch sizes in model designs. The figure shows that the LSTM has lower loss values relative to MLP model whenever the epoch size increases from 40 onwards. The MLP has not visible progresses while the epoch is increased due to lower learning capacity. The LSTM network has better learning capacity due to integrative works of its gates such as input gate, output gate and forget gate, and its deeper learning capacity and learning principles. As a result, the LSTM can make performance differences in each larger epoch numbers over MLP algorithm. Figure 5 shows the performances of MLP and LSTM models compared to the real path of the mobile carriers. The black dotted line is the real path of the mobile user. The red color is the MLP based mobility predictions. The blue line shows the LSTM algorithm performances in the corresponding testing points. The MLP result shows more fluctuations and the results

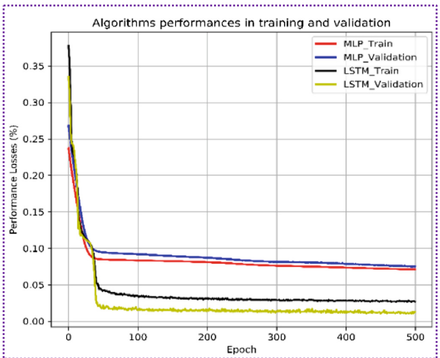

Fig. 4. The MLP and LSTM performances in mobility predictions

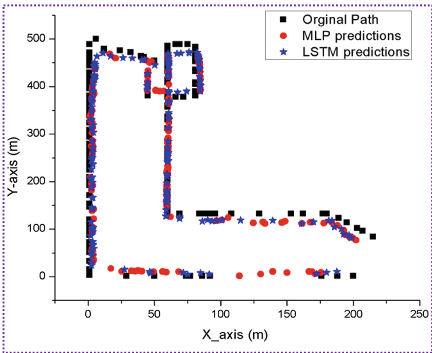

Fig. 5. Mobility prediction compared to actual path (Color figure online)

in each testing points are unstable relative to LSTM model. While there is bended paths in the working areas, the LSTM outperforms and nearly parallel as well as overlap with the actual paths.

The result implies that the MLP has lower adaptability while it has much possible hidden layers and other similar properties. However, this does not mean that MLP is useless. The higher performances behind LSTM algorithm are due to its gates and deeper learning capacity to the nonlinear datasets. Local maxima does not affect the LSTM model easily while this is a common trouble of MLP. The main implication of LSTM's outperformances is that the validation loss function is smaller than the training loss function, which is uncommon to most machine language models. The LSTM performance in Fig. 5 and Table 2 are the good implications.

In Table 2, the MSE and MAE are shown for both MLP and LSTM algorithms. In each evaluation parameters, the LSTM has better performances. Thus, the LSTM can provide motivated results in average as well as at distinct testing points, as shown in Table 2 and Fig. 5, respectively. Note that, in the models evaluations procedure, we used similar ranges of epoch, hidden layers, activation function and optimizers to avoid performance evaluation's biasedness.

Table 2. The MLP and LSTM performances in mobility predictions in m.

Algorithms	MSE	MAE
MLP	0.20	0.25
LSTM	0.0003	0.012

4 Conclusions and Future Works

In this paper, we evaluated the performance of LSTM algorithm for mobility prediction using cellular network data collected from UAV-BSs. The data is collected experimentally. The simulation results show that the proposed method can work well and it can cope the dynamical changes of environments. The proposed technique provides the state-of-the-art performances in distinct as well as bounded system performances. In the future work, we propose for mobility prediction of IoT devices through integration of IoT devices.

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