Mobility State Classification in HetNets Using Machine Learning

Syed Maaz Shahid and Sungoh Kwon
Department of Electrical, Electronic and Computer Engineering, University of Ulsan, Ulsan 44610, South Korea.
e-mail: maaz.shahid26@gmail.com; sungoh@ulsan.ac.kr

***Abstract*—Ultra-dense small cell deployment in 5G networks leads to heterogeneous networks (HetNets) and makes mobility management more complex. Supporting seamless connectivity to diverse mobile users in HeNets by optimizing handover performance is one of the major challenges of mobility management. Knowledge of the mobility state of users for the handover process increases the handover performance since handover control parameters settings depend on user speed. In this work, a machine learning algorithm is used for classifying users' mobility states into one of three mobility states defined by 3GPP in HetNets. Users' sojourn times in small cells are used to train the feedforward neural network. The simulation results show that using cell sojourn time, the proposed feedforward neural network achieves satisfactory performance.**

I. Introduction

Mobility management has emerged as one of the most critical challenges in heterogeneous networks (HetNets) due to the deployment of small cells in the traditional macro cell-only networks to meet the demand for wireless data from billion of user equipments (UEs) [1]. Mobility management is required to ensure continuous connectivity to mobile UEs for a higher quality of service (QoS). Utilizing the mobility context in terms of UE's speed range for mobility management not only optimizes handover performance, especially in HetNets but also helps for efficient resource scheduling, load balancing, and energy efficiency enhancements [2]. The 3rd Generation Partnership Project (3GPP) specified a mechanism to detect UE speed range, referred to as mobility state estimation (MSE), based on the number of handovers over a specified period of time [3]. In MSE, three mobility states are defined based on handover counts: a normal mobility state, a medium mobility state, and a high mobility state. The baseline procedure of MSE is insufficient for HetNets to differentiate UE's mobility state because of the different sizes of cells and UE mobility behaviors.

The diversity of user behaviors in terms of movement trends imposes a challenge to establish a mechanism to detect the mobility state of UEs. Consider a scenario in Figure 1, UE1 and UE2 are both moving with the same speed and different trajectories. UE2 experiences more handovers than UE1 in a predefined interval, leading to the overestimation of the mobility state for UE2. A weighting-based MSE procedure was proposed for HetNets in [4] to enhance the existing MSE scheme, where different weight factors are assigned to different handover types giving higher weight for macro-to-macro handovers and smaller weights for handovers involving small cells. The weighting-based MSE did not incorporate the UE trajectory, which led to an incorrect estimation of UE mobility. An enhanced MSE approach was proposed to consider the UE trajectory in [5]. However, only a linear trajectory was assumed, which is unrealistic.

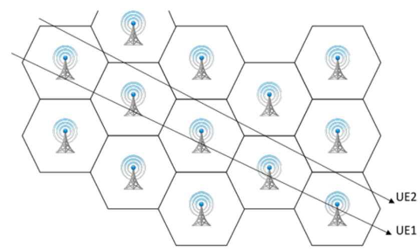

Fig. 1. UEs with same speed and different linear trajectories [5].

In this paper, we utilize a machine learning algorithm to classify UE mobility states in HetNets. To detect a UE mobility state in real-time, small cells' sojourn time from user history information is utilized instead of handover counts to tackle the dynamic user mobility behavior. A shallow feedforward neural network is designed and trained, which achieves an accuracy of more than 93% on the test set.

II. System Model and Problem Description

We consider a two-tier HetNet that includes both macro cells and small cells. The cells in the network are interconnected through the X2 interface, which allows them to directly communicate with each other and perform functionalities such as handovers, load management, mobility optimization, etc. As a result, UE handovers can take place between macro cells and small cells, between small cells, and between macro cells, as well, for seamless connectivity. We considered the computing, storage, and networking resources are integrated with the base station using mobile edge computing. We ignore the dual connectivity capability of UEs in this study, therefore UEs are only paired with one cell at a time. In addition, each UE is associated with one of the mobility states out of three mobility states and moves within the network.

In this work, we focus on the training of the artificial neural network (ANN) model for mobility state detection of UEs. The aim is to minimize the cross-entropy loss, i.e., an error between actual and predicted output, by training the ANN model with the training data. We assume that each UE has available data, e.g., the user history information [6].

TABLE I
PERFORMANCE OF FEEDFORWARD NEURAL NETWORK ON THE TEST SET

Accuracy (%)	**Precision** (%)
93.80	93.76

III. MACHINE LEARNING-BASED MSE SYSTEM EVALUATION

A. Experimental Setup and Training Data Set

We consider a scenario of a dense urban consisting of seven macro cells and 42 small cells. Macro cells are located with an inter-site distance of 1000m, and 8 small cells are uniformly and randomly located in each macro cell. We considered a random waypoint mobility model that allows each UE to follow a different trajectory. A bouncing rectangle is used to keep the UEs within the network such that UE chooses the destination within the bouncing rectangle. A UE with a speed between 1.8 km/h to 30 km/h is considered to be in normal mobility state [5]. A UE with a speed of more than 31 km/h and less than 60 km/hr is considered to be in a medium mobility state and UE in high mobility state has a speed between 61km/h to 120 km/h [5].

To collect the training data, we simulate the scenario with 500 UEs for each mobility state one by one. The simulation time is set to 30 minutes. After 10 minutes of the simulation, user information including serving cell ID, time instances at which UE connected to the cell, and leaving the cell are stored in the log file. A training data set has 5,000 samples for each mobility state, which are collected from UEs history information at 10 different instances with a minimum interval of one minute. The data set consists of a total of 15,000 samples, which are divided into two sets: a training set and a test set. The training set has 80% of the total data and the remaining data is used for a test set.

For machine learning architecture, a shallow feedforward neural network is implemented to reduce the time complexity of the model. The hidden layer has 150 neurons and the rectified linear unit (ReLU) activation function is used in the hidden layer. To get the output of the network, a softmax function as an activation function is used in the output layer to predict the probability distribution over output classes. The sojourn time of UEs in previously visited small cells is considered the input feature for the training of the feedforward neural network to classify the UE mobility state.

B. Performacne of Feedforward Neural Network

The performance of the trained feedforward neural network on the test is shown in Table I. The trained neural network architecture achieves a test accuracy of 93.80%. A confusion matrix for the test set is shown in Figure 2, which illustrates the classification accuracy of the trained ANN on each class of the test set. Some samples of low-mobility and high-mobility states are classified as medium-mobility states by the ANN. This is because some UEs associated with low mobility and high mobility states have speeds close to lower and upper-speed ranges of the medium mobility class. Similarly, 81 samples of the medium mobility class are wrongly classified.

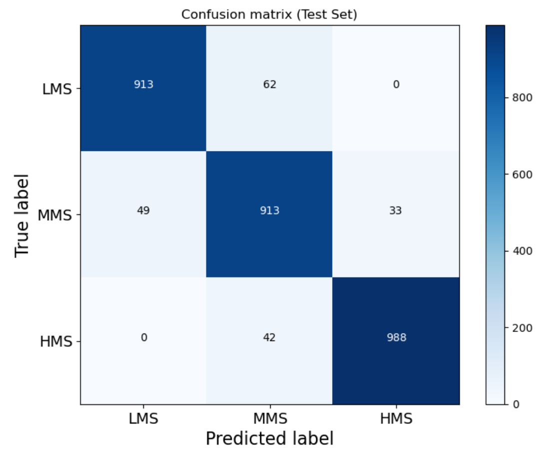

Fig. 2. Confusion matrix for the test set.

The accuracy for low and high mobility classes is 93.64% and 95.92%, respectively, and the prediction accuracy for a medium mobility class is 91.76%. Overall, the misclassification rate of the neural network is 0.0620.

IV. CONCLUSION

In this paper, we used a machine learning algorithm for the classification of UE mobility states in HetNets. The UE history of small cell sojourn times is utilized as input features to train ANN. Simulation results showed that the sojourn time in previously visited small cells is a relevant feature for the classification of user mobility state in HetNets. The trained feedforward neural network has shown an accuracy of more than 93% on the test set. The result of this study is used to update the handover parameters to increase network performance.

REFERENCES

[1] Y. Li, Y. Zhang, K. Luo, T. Jiang, Z. Li, and W. Peng, "Ultra-dense hetnets meet big data: Green frameworks, techniques, and approaches," *IEEE Communications Magazine*, vol. 56, no. 6, pp. 56–63, 2018.

[2] I. Saffar, M. L. A. Morel, K. D. Singh, and C. Viho, "Deep learning based speed profiling for mobile users in 5G cellular networks," in *2019 IEEE Global Communications Conference (GLOBECOM)*, 2019, pp. 1–7.

[3] 3GPP, "5G NR; User Equipment (UE) procedures in idle mode and in RRC Inactive state," 3rd Generation Partnership Project (3GPP), Technical Specification (TS) 38.304, 03 2021, version 15.0.0. [Online]. Available: https://portal.3gpp.org/

[4] S. Barbera, P. H. Michaelsen, M. Säily, and K. Pedersen, "Improved mobility performance in lte co-channel hetnets through speed differentiated enhancements," in *2012 IEEE Globecom Workshops*, 2012, pp. 426–430.

[5] P. S. Deogun, M. Mehta, A. Karandikar, and N. Akhtar, "Trajectory based mobility state estimation for heterogeneous cellular networks," in *2016 IEEE Wireless Communications and Networking Conference*, 2016, pp. 1–6.

[6] 3GPP, "Technical Specification Group Radio Access Network; NR; Radio Resource Control (RRC) protocol specification," 3rd Generation Partnership Project (3GPP), Technical Specification (TS) 38.331, 09 2020, version 16.0.0. [Online]. Available: https://portal.3gpp.org/

ACKNOWLEDGMENT

This research was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (NRF-2021R1I1A3A04037415).