Mobility Prediction using Artificial Neural Network in Mobile Communication Network

Hee-Seon Jang

Abstract**—** This paper proposes a method of predicting the movement direction between cells of subscribers (UE, user equipment) for efficient mobility management in mobile communication networks. To predict the moving direction of UE, an artificial neural network model is developed by using R programming language, and location registration and paging costs (signaling bits) for each UE collected are used as dependent variables. In addition, the paging scheme considers the method of paging the incoming calls to the UE at once (simultaneous paging) and the method of paging it twice (selective paging). In addition, softmax is used as an activation function, and a weight reduction method is used to prevent overfitting to construct neural network. From the numerical results, it is observed that the total cost in the selective paging is reduced by about 17.2% compared to the simultaneous paging method. And, as a result of evaluating the accuracy of the model using validation dataset, the accuracy is 63.43% in the simultaneous paging, and the prediction accuracy is improved to 82.9% by confirming the UE at the boundary of the tracking area by using the twostep selective paging technique.

Keywords**—** mobility prediction, location registration, paging, artificial neural network.

I. Introduction

To meet the increasing mobile users (user equipment, UEs) in highly dense mobile communication network, location management plays a fundamental role in 5G networks [1,7]. Tracking UE's location requires considerable efforts, and it consists of two tasks: location registration and paging. To keep track of UE's location, the service area is divided into non-overlapping areas called tracking areas (TAs) that includes several cells. The location registration is to update the location (TA list, TAL, group of TAs) where the UE is located. The location registration procedure is performed whenever the UE moves to a TAL that does not belong to the previously registered list. In addition, when the call arrives to the UE, through the paging process, the broadcast messages from the last TAL where UE were registered. So far, many studies have been proposed to reduce registration and paging costs [3,4,5,9]. Among them, it can be observed that the performance of the registration scheme using the moving probability of the UE is superior to that of the existing zone-based [5] or distance-based method [6]. However, in related studies, no method was suggested to predict the moving probability of UEs. Therefore, in this study, an artificial neural network model that predicts the movement direction of UEs using cost (number of signalling bits) values such as registration and paging cost is presented. In the proposed neural network model [2,8], previously used experimental data [3] are used to classify into learning and validation dataset and analyse the prediction performance of the proposed model.

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II. Artificial Neural Network Analysis to Predict Moving Direction

A. 5G Mobile Communication Network

Figure 1 shows the architecture of 5G mobile communications network [1,7]. The access and mobility management function (AMF) manages mobility of subscribers, and it performs mobility management functions through two main functions: location registration and paging. In order to provide a successful mobility management services, the mobile communications network is divided into tracking area (TA) that do not overlap each other. And a few TAs form a single TA list (TAL). The location registration process is performed when a UE moves to an area that is not in the list stored in the AMF. When the incoming call arrives at the UE, the paging procedure is performed. The AMF transmits a paging (or broadcast) message through a base station belonging to all TAs stored in the TAL.

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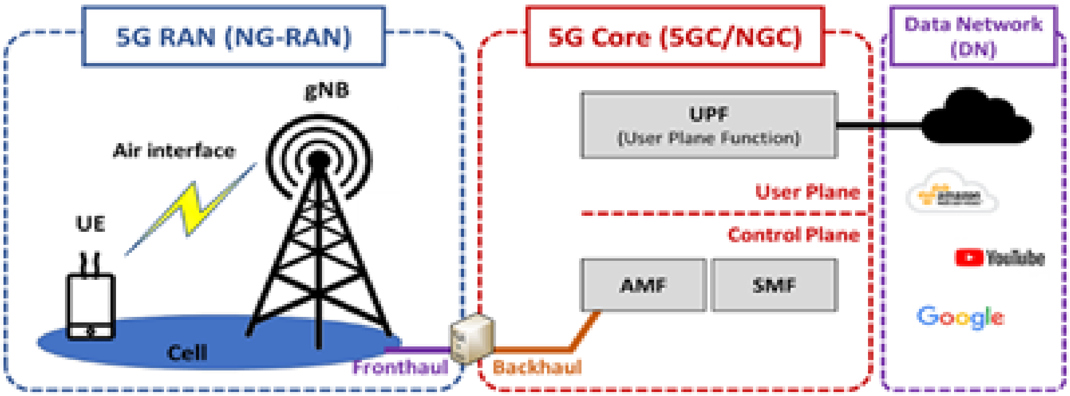

5 Generation Core(5GC), Access and Mobility Management Function(AMF), Next Generation Core(NGC), Next Generation Node B(gNB), Next Generation Radio Access Network(NG-RAN), Session Management Function(SMF), User Equipment(UE)

Fig. 1: 5G mobile communications network

B. Mobility prediction in registration scheme with flexible TAL forming

Various results have been proposed for mobility management schemes to minimize the total signalling cost, for example, zone-based [5], movement-based [9], distance-based [6], and TAL-based registration [3,4]. Among them, Jang and Baek [3] proposed a flexible TAL-forming registration method to reduce the total signal cost of automobile users in LTE advanced communication networks, using the direction of travel information in UE. In this method, the movement direction of the UE could be predicted based on a known geographic area of the trace, a map and movement statistics of the UE. For example, assuming that TA is composed of one cell for convenience of analysis, Figure 2 shows that more subscribers move from cell 1 to cell 3 at rush hour than other cells. In the flexible TAL forming registration scheme, a UE can move to middle cell (cell 3) at an angle of 60o, and a predictive direction of q under the compact road structure of the sector. The following mobility models are adopted.

1) The UE predicts the movement direction in cell 1 using the data available so far, and configures a new TA accordingly. The UE moves from cell 1 to cell 3 with a probability of *q*.
2) After that, the UE randomly selects and moves one of the six directions by the random walk model, and repeats the above process in the new cell (TA).

In this paper, we would like to predict the probability *q* of movement from cell 1 to cell 3 by using data of average registration cost and paging cost (number of signalling bits/UE/hr) for each UE using artificial neural network. In addition, in this study, two paging methods are considered as follows. First, the method of paging all seven cells registered by the UE when the incoming call arrives is called “onestep simultaneous paging”, and the method of paging to the middle cell (cell 3) first and to the remaining six cells if there is no response from the UE is called “twostep selective paging”. Note that the twostep selective paging method has a lower total cost than the simultaneous paging scheme.

Experimental data used in the study [3] are used to develop neural network. Figure 3 shows the data used in this study, and shows the (*regist*, *paging1*, *paging2*, *total1*, *total2*, *enterq*) = (registration cost, onestep paging cost, twostep paging cost, total cost in onestep paging, total cost in twostep paging, *q*) for 10,000 mobile subscribers. Here, *enterq* is a factor variable that has a value of 1 when the UE actually moves from cell 1 to cell 3, and has a value of 0 when moving to another cell other than cell 3. In the case of selective paging, the average paging cost (*paging2*) is 5.64, which is about 19.4% lower than the simultaneous paging cost (*paging1*=7), and the total cost is also reduced by about 15% from 9 to 7.65.

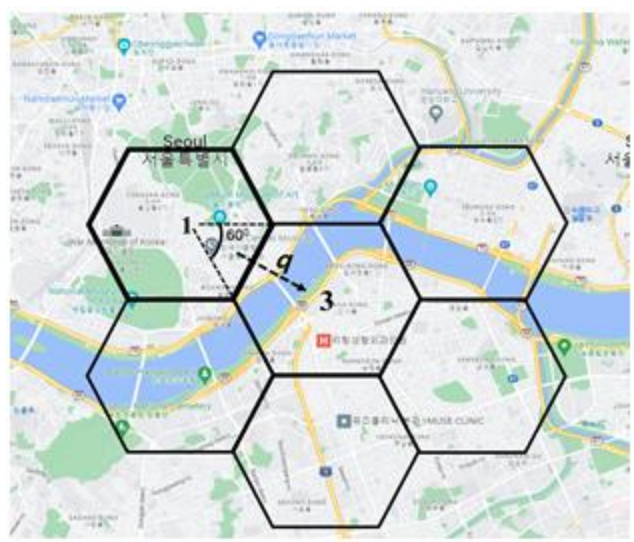

Fig. 2: Moving UEs around the rush hour in Seoul.

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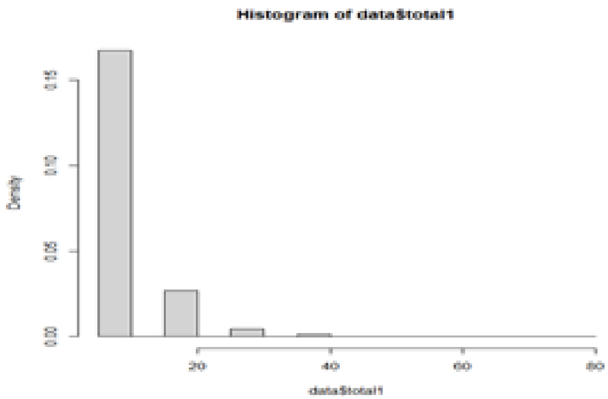
```
> describe(data1)
         vars     n mean   sd median trimmed mad min max range  skew kurtosis   se
regist      1 10000 2.00 5.05      0    0.79   0   0  70    70  3.16    14.03 0.05
paging1     2 10000 7.00 0.00      7    7.00   0   7   7     0   NaN      NaN 0.00
paging2     3 10000 5.64 2.51      7    6.06   0   1   7     6 -1.31    -0.28 0.03
total1      4 10000 9.00 5.05      7    7.79   0   7  77    70  3.16    14.03 0.05
total2      5 10000 7.65 5.60      7    6.89   0   1  77    76  2.21     9.62 0.06
enterq      6 10000 0.39 0.49      0    0.36   0   0   1     1  0.47    -1.78 0.00
```

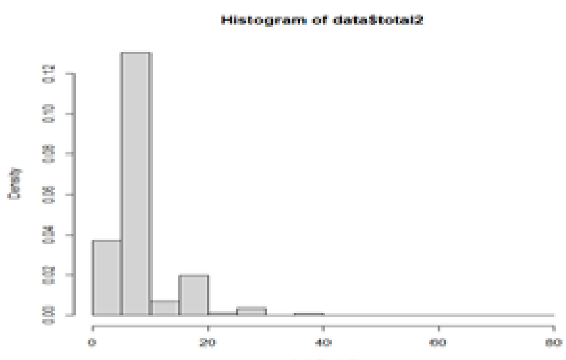
sd: standard deviation, trimmed: trim means by dropping the top and bottom fraction (10% cutting average), mad: median absolute deviation, se: standard error(=sd/sqrt(n))

Fig. 3: Descriptive Statistics for Experimental Data

Figure 4 shows a comparison of the total costs of the onestep paging and the twostep paging methods using the density function graph. From the results, it can be observed that there are more intervals in which the value of the total cost in the selective paging method has a smaller value than in the simultaneous paging. In Figure 4, the result of “*accuracy()*” function represents the (mean of errors(ME), root mean of squared errors(RMSE), mean of absolute errors(MAE), mean of percentage errors(MPE), mean of absolute percentage errors(MAPE)) of the total signalling cost value for the two paging schemes. Note that the total cost in the selective paging is reduced by about 17.2% compared to the total cost in the simultaneous paging method.



Total cost for the simultaneous paging (onesetp)



Total cost for the selective paging (twostep)

```
> accuracy(data$total1, data$total2)
              ME     RMSE    MAE       MPE     MAPE
Test set -1.3554 2.851736 1.3554 -112.9929 112.9929
> rel_improvement <- abs((data$total1-data$total2)/data$total1) * 100
> mean(rel_improvement)
[1] 17.20146
```

Fig. 4: Total signalling cost according to paging methods

C. Simultaneous paging

A neural network as shown in Figure 5 is used to predict the probability (q) of the moving to the middle cell in the simultaneous paging method. In the figure, the number on the edge represents the weight between the two nodes. Location registration cost (*regist*), paging cost (*paging1*), and total cost (*total1*) are used to predict q in the developed model. In the proposed neural network, the “*nnet()*” function provided by the *R* packages [2,8] is adopted. The *nnet* uses a single-hidden layer neural network, optimizes the parameters of the network using a sum of squared errors, uses a softmax function as an output results (activation function), and uses a weight reduction method to prevent overfitting. To determine the performance of the developed neural network, 70% of the total 10,000 UE’s data is used for training, the remaining 30% is used for testing data, and the accuracy of predictions for validation data is measured. As a result of neural network in Figure 5 for validation dataset, the accuracy of the prediction result is 63.43%. In addition, area under the receiver operating characteristics (ROC) curve (AUC) is evaluated as 0.5613, and the model developed is to be considered somewhat lacking in discrimination.

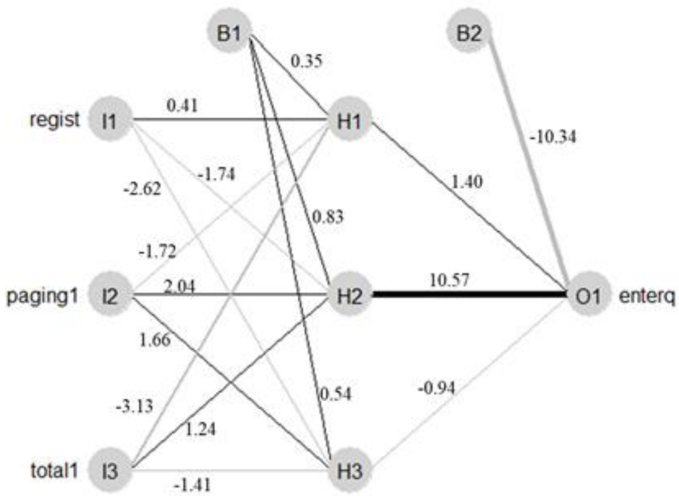


Fig. 5: Neural network to predict the moving direction in the simultaneous paging

D. Selective paging

In the same manner, the neural network model of the twostep selective paging scheme is shown in Figure 6, and registration (*regist*), paging (*paging2*), and total cost (*total2*) are used to predict *q*. Figure 7 shows the ROC curve and AUC value. Note that, in the ROC curve, the closer the shape of the curve is to the upper left, the higher the accuracy of the model. From the results, it is observed that the accuracy of the prediction performance is improved to 82.9% compared to the simultaneous paging method. And, the neural network model used with AUC=0.7806 is evaluated as a data prediction analysis model with good performance. The reason why the prediction performance is improved is that the prediction accuracy is improved by using the paging information of the UE in cell 3 and paging information in the remaining 6 cells compared to the simultaneous paging scheme. Note that, in the simultaneous paging, when an incoming call arrives to a UE, the incoming call to a subscriber is connected to the subscriber only once by paging seven cells at the same time, and accordingly, the paging cost of all UEs is the same. On the other hand, in the selective paging method, the UE can connect the call only once if it is in cell 3, and twice if it is in the remaining six cells. Therefore, it is possible to know whether the subscriber is currently in the cell 3 or at the boundary of the location area (TAL). In addition, in the selective paging, by using such UE’s location information, the probability of UE’s movement can be more effectively predicted compared to simultaneous paging method.

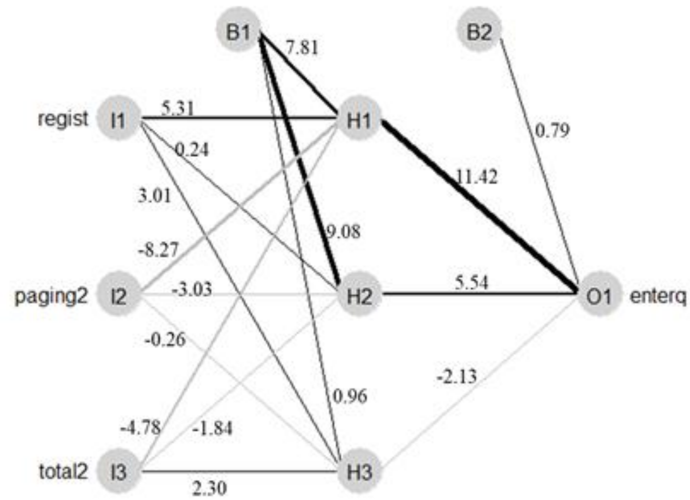
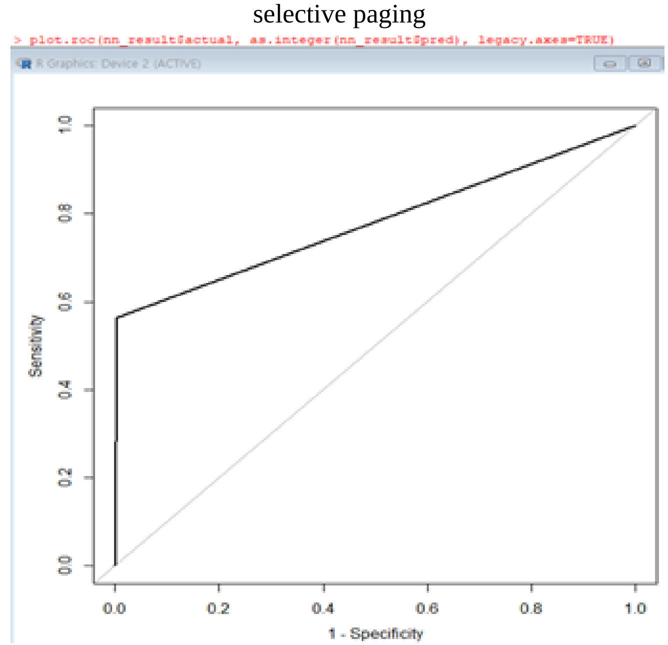


Fig. 6: Neural network to predict the moving direction in the selective paging




```
> roc(nn_result$actual, as.integer(nn_result$pred))$auc
Setting levels: control = 0, case = 1
Setting direction: controls < cases
Area under the curve: 0.7806
```

Fig. 7: Receiver operating characteristics curve (ROC) and AUC value in the selective paging

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