DNN-BASED WIRELESS POSITIONING IN AN OUTDOOR ENVIRONMENT

Jin-Young Lee[1], *Chahyeon Eom*[1], *Youngsu Kwak*[2], *Hong-Goo Kang*[1] *and Chungyong Lee*[1]

[1]Department of Electrical and Electronic Engineering, Yonsei University, Seoul, Korea
[2]Innowireless Co. Ltd., Seongnam-si, Gyeonggi-do, Korea

ABSTRACT

In this paper, we propose a deep learning based algorithm to estimate the position of an user by utilizing reference signal received power (RSRP) and the location of base stations. To obtain reliable results in a real communication environment, parameters were measured using commercially available base stations and mobile phones within a LTE network. Since the structure of the measured data changes in accordance with the number of connected base stations, it is necessary to work on data uniformity processing before running the deep learning network. Therefore, we extract only the case in which three base stations are connected, using it as a feature of deep learning network. The experimental results reveal that the performance of the proposed algorithm is much better than that of the conventional fingerprint method. The average distance error is reduced from 71.04 meters for the fingerprint-based method to 43.51 meters for the proposed deep learning-based method.

Index Terms— deep neural network, outdoor positioning, wireless positioning, field measurement, reference signal received power

1. INTRODUCTION

Smart phones are becoming an essential part of daily human life. In order to provide a standard quality of service for users, the communication environment's coverage needs to be expanded by increasing the number of base stations at proper places. Conventionally, drive test was performed to optimize the network infrastructures; however, it is labor-intensive and costly. To reduce costs, the minimization of drive tests (MDT) was specified in the 3rd Generation Partnership Project (3GPP) [1] allowing for the continuous and automatic monitoring of the radio status of each user's device.

In order to draw a coverage map using MDT data, it is very important to identify the location of user's device. It is trivial to obtain the exact location if we use global navigation satellite system (GNSS) for MDT data [2]. However, when the user turns off the GNSS functionality, the location of the user equipment (UE) has to be estimated through the use of other information made available through MDT measurements. For example, it is possible to estimate the location of the UE by utilizing the received signal strengths (RSSs) of multiple base stations. There are many positioning methods that use RSS including triangulation and fingerprint-based positioning method [3][4][5][6]. However, since RSS varies greatly depending on the surrounding environment, it can be complicated to determine the exact location of the UE using the conventional approaches.

In this paper, we estimate the location of the UE using reference signal received power (RSRP) and the location of base stations with a deep neural network (DNN) structure. DNN successfully finds a non-linear relationship between any input and output parameters if the training database is sufficient enough. Due to this characteristic, DNN has also been applied to wireless positioning researches [7][8][9]. However, it has never been used for the scenario in an outdoor LTE environment, especially using the measured data in a real communication field. The proposed algorithm utilizes three of the strongest RSRPs and their corresponding base stations' latitudes and longitudes for the input and the latitude and longitude of the UE for the output parameters of the DNN. Before the network is trained, all the input data are first normalized in order to have zero mean and unit variance. In consideration of the fact that these parameters are temporally related, data in consecutive frames are simultaneously used with a context window. In order to verify the actual performance of the proposed algorithm, we measured the data from a commercial LTE communication system, which was operated in 1800 MHz band.

This work was supported by the ICT R&D program of MSIT/IITP, Republic of Korea. [2017-0-00377-001, AI based wireless network quality monitoring system]

2. BACKGROUND

2.1. Overview of minimization of drive tests

MDT, which was first introduced in 3GPP Release 10, is a solution that allows for the monitoring of the status of received radio with commercial devices for the purpose of optimizing network parameters [10]. Fig. 1 depicts a simplified MDT architecture that consists of operation and maintenance (OAM), radio access network (RAN) node, trace collection entity (TCE) and UE [10]. OAM determines the configura-

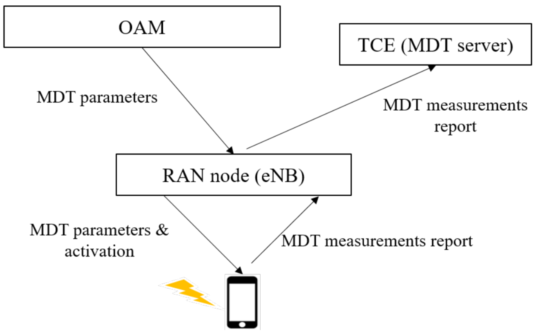


Fig. 1. Flow of MDT protocol.

tion of MDT parameters for the UE to measure and then sends these parameters to the RAN node. The RAN node, which is also known as an evolved node B, is a base station within LTE network. The RAN node receives the parameters and then sends them to the UE in order to activate the MDT functionality of the UE. The UE then reports the measured data to the RAN node. This data is finally sent to the MDT server, which is the TCE [11].

Among many parameters available in the MDT data format, we can use RSRP and physical cell id (PCI) in order to estimate the location of UE. RSRP is defined as the linear average over the power contributions of the resource elements that carry cell-specific reference signals [12]. PCI is an identifier of a cell at physical layer indicating which base station the UE is connected to. Through PCI, the latitudinal and longitudinal of the base station is provided.

2.2. Conventional fingerprint-based localization

Fingerprint-based localization matches the observations of geotagged signatures to a map of previously measured signatures [6][13][14][15][16]. This type of localization displays relatively high performance if an accurate database is available [13]. In this paper, we deploy the grid-based fingerprint scheme.

The localization process is divided into training and matching phases. The training phase exploits measured signatures in order to create a database for each grid unit. The region is made up of pre-defined square grid units, and the signature of each grid unit is saved in the training databases. In other words, each grid point is represented by one training signature vector such as RSRPs and their corresponding base stations, PCIs. Next, each grid unit's signature is mapped to the longitude and latitude of the middle point of the grid unit.

During the matching phase, the location of the UE is estimated by the discovery of the best matching signature. In order to determine the best matching signature in the training database, the test signature vector that has the same configuration as the training phase is compared to each training signature vector. Next, the grid point is searched by a pattern matching algorithm in order to determine the grid unit that has the minimum Euclidean distance among the grid unit candidates that have the same PCI set [16].

Table 1. Field measurement format.

Parameter		Description
EARFCN (UL, DL)		Uplink or downlink frequency as E-ARFCN
Bandwidth (UL, DL)		Uplink or downlink bandwidth as E-ARFCN
Band		Band as E-ARFCN
Top set	PCI	Top 1 to 20
	RSRP	Top 1 to 20
	RSSI	Top 1 to 20
	RSRQ	Top 1 to 20

2.3. Deep neural network

Deep neural network has been successfully used for modeling complicated relationship between input and output values when a large amount of data is available to train the network. A DNN consists of input, output, and hidden nodes. To model a function using DNN, the neural network has to be trained by adjusting the weight values via the input and output values. The DNN training process is divided into two stages.

The first stage is the feed-forward stage. This is the process of calculating the output value of the current network from the input layer to the output layer. The feed-forward is implemented by the following equation:

$$h = f(W_{xh}x + b_h) \quad (1)$$

$$y = W_{hy}h + b_y, \quad (2)$$

where x, h, y, W, b and f are the input vectors, hidden vectors, output vectors, weight matrices, bias vectors and hidden layer activation function, respectively (e.g. W_{xh} is the input-hidden weight matrix and b_h is hidden bias vector). Since the activation function models the nonlinear relationship between the input and output values, as well as the fact that these operations are repeated from the input layer to the output layer, a DNN effectively models the nonlinear function.

The second stage is the back-propagation stage. This is the process of calculating the difference between the output value and the true value and updating all the weights from the output layer to the input layer so that the difference is minimized. The gradient descent method is used to minimize the cost function.

3. PROPOSED DNN-BASED LOCALIZATION

3.1. Field measured data analysis

The format of field measured data is represented in Table 1. Among these parameters, we use PCI and RSRP of Top set. The number after 'Top' indicates the order according to the

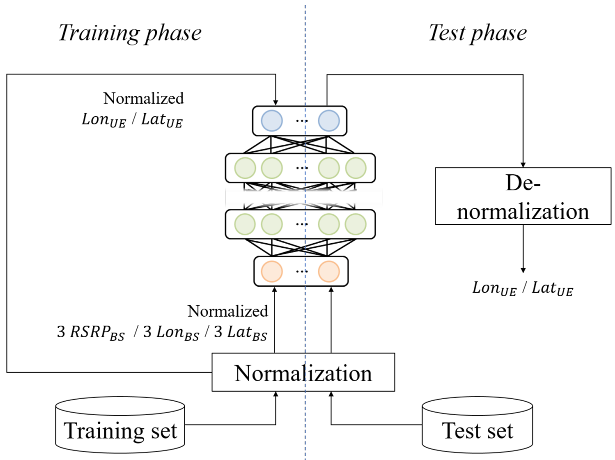
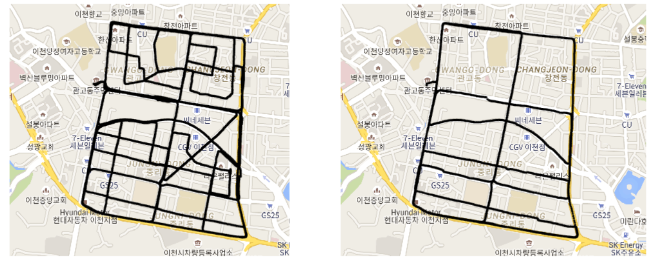


Fig. 2. Block diagram of DNN training and test.

strength of the RSRP. However, the number of base stations connected to the UE changes every moment depending on the surrounding environment. In field measured data, only one station is connected in 82.74% of cases, two stations are connected in 10.65% of cases, and three stations are connected in 4.82% of cases. The portion of the data connected to more than three base stations is too small and the data connected to two base stations lacks information for predicting the position of the UE. Accordingly, in this paper, we utilize the data of three connected base stations. However, the time interval between the consecutive data changes as a result of the discarded data. Our raw data was transmitted with an average of 77.01 times per second. After extracting the data that had three connected base stations, the remaining data were measured with an average of only 3.83 times per second. When the time differences between two consecutive samples were measured using time stamps, most of them were placed within one second; however, sometimes the difference lasted longer than a minute. Therefore, it is necessary to compensate for this difference when training a DNN network.

3.2. DNN training and test

Fig. 2 illustrates the training and test method of the DNN structure for positioning. During the training stage, all the features for the training set are normalized to have zero mean and unit variance. The RSRP, latitude and longitude of the Top 1 to 3 base stations are used as DNN input features, which are symbolized by $RSRP_{BS}$, Lon_{BS} and Lat_{BS}. The latitude and longitude of the UE are used as DNN output features, which are symbolized by Lon_{UE} and Lat_{UE}. Next, the DNN network repeats feed-forward and back-propagation continuously, updating the weight and bias values so that the output data of the input features, which are calculated by the network, are close to the target data. During the test stage, the input features are normalized to have zero mean and unit variance in order to match the training process. Finally, we obtain the estimated latitude and longitude values through the



(a) Data measured in detai (b) Data measured sparsely.

Fig. 3. Drive trajectory of the field measurements.

Table 2. Database and DNN network setup.

# of samples	detailed DB	26,061 (S5_A)
		22,297 (S5_B)
		31,511 (G5)
	sparse DB	10,875 (S5_A)
Input layer		9 dimensions
Output layer		2 dimensions
Normalization		Zero mean, unit variance
Weight initialization		Xavier
Activation function		ReLU
Optimizer		Adam
Cost function		MSE

trained network.

We also extend the proposed algorithm to have a context window that uses past and future features, as well as the current DNN input feature. The rationale behind this idea is that the RSRP data is a time series; thus, the past and future input features are correlated with the current output features.

4. EXPERIMENTS

4.1. Simulation setup

The field measurements were performed using 1800 MHz LTE bands in Icheon-si, Gyonggi-do, Republic of Korea on Aug. 2017. The measured area was about 910 meters east to west and 1100 meters north to south. The measurements were performed twice. The initial measurements took into account almost all roads in detail, using three devices (two Samsung Galaxy S5s and one LG G5). The secondary measurements were relatively sparser than the first ones, using one device (a Samsung Galaxy S5). We call these data sets "detailed DB" and "sparse DB", respectively. The two drive routes are shown in Fig. 3. The devices were connected to an average of 1.34 base stations on a time stamp, and the median distance between the serving cell and the UE was about 105.16 meters.

These experiments are performed in several ways. The first experiment is to compare the performance variation of the DNN network when the number of nodes and the number

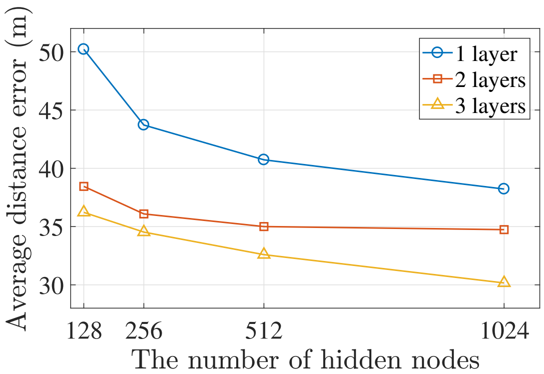


Fig. 4. Average distance errors for various nodes and layers.

of layers are adjusted. The number of nodes was experimentally increased from 128 to 1,024, and the number of layers was increased from 1 to 3. Three detailed DBs with 5-fold cross validation were used to prevent over-fitting and to compare performance fairly. The second experiment is to compare the performance by changing the size of the context window. The size is changed from (0+1+0) to (4+1+4) to find the proper length of context window. The (4+1+4) means to use the current features with four frame features before and after the current frame. The (0+1+0) means to use only the current frame features. The third experiment compares the performance of the proposed localization method to that of the conventional fingerprint-based method.

Table 2 shows the setup of the DNN network. In all experiments except the first one, we used the DNN networks having 3 layers with 1,024 nodes each, 3 detailed DBs as a training set, and the sparse DB as a test set. The number of training set is 79,869 and the number of test set is 10,875.

4.2. Simulation results

Fig. 4 displays the result of the first experiment. An average distance error between the estimated position and the target position in metric units is used to determine representative performance. The performance improves as the numbers of nodes and layers increases. Of course, the complexity increases exponentially as the number of layers increases.

Table 3 shows the results of the second experiment. The average distance error and distance errors for 70% and 90% of cumulative distribution function of distance error between the estimated position and the actual location obtained by GNSS are represented in metric units. In case of using the context window (1+1+1), the performance was found to be the best. However, the results also show that performance does not improve when the size of the context window is increased. This is due to the time discontinuity caused by discarding the data if they do not include the parameters from at least three base stations. In order to compensate for this discontinuity, a data interpolation method or preprocessing with successive sequences is required. It remains our future work.

Table 3. Performance with different context window size.

Context window	Average distance err.	Distance err. for 70%	Distance err. for 90%
(0+1+0)	51.70 m	56.37 m	119.73 m
(1+1+1)	43.51 m	42.33 m	98.97 m
(2+1+2)	45.09 m	44.17 m	105.47 m
(3+1+3)	45.78 m	46.41 m	102.19 m
(4+1+4)	47.51 m	46.47 m	108.12 m

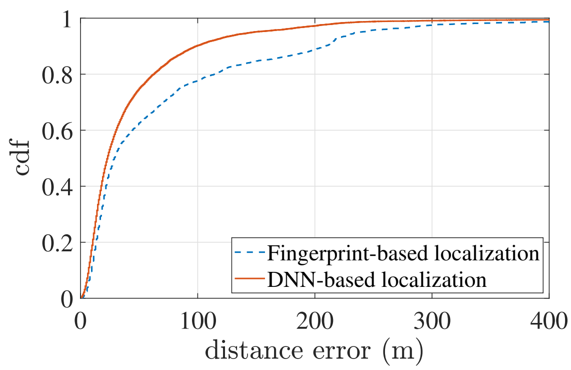


Fig. 5. Cumulative distribution function of distance error.

In the third experiment, the fingerprint-based method that uses RSRP measurements of the Top 1 to 3 base stations with a 10-by-10 meters grid unit was used to compare the performance with the proposed algorithm. A context window of (1+1+1) is applied to the DNN input layer. The average distance error is 71.04 meters for the fingerprint-based method, and 43.51 meters for the DNN-based method. The cumulative distribution function of the distance error is plotted in Fig. 5, demonstrating that the distance error is reduced from 72.14 meters to 42.33 meters for 70% and the distance error is reduced from 208.5 meters to 98.97 meters for 90% using the DNN-based localization method when compared with fingerprint-based localization method. It is obvious that the proposed DNN structure predicts the location of the UE better than the fingerprint-based method.

5. CONCLUSION

This paper has proposed a DNN structure that can predict the location of an UE using RSRP data and the locations of the base stations. Since field measurement data obtained by commercial base stations and UEs were used in these experiments, the results fully represent the outcomes that can be actually obtained in real environments. The experimental results demonstrated that the average distance error of the proposed algorithm could be reduced by 27.53 meters in comparison to the conventional fingerprint-based localization method. We are going to increase the amount of training database and use additional environment-related features in order to further improve the performance.

6. REFERENCES

[1] 3GPP, "Evolved Universal Terrestrial Radio Access (E-UTRA); Study on minimization of drive-tests in next generation networks," Technical Specification (TS) 36.805, 3rd Generation Partnership Project (3GPP), 01 2010, Version 9.0.0.

[2] 3GPP, "Universal Terrestrial Radio Access (UTRA) and Evolved Universal Terrestrial Radio Access (E-UTRA); Radio measurement collection for Minimization of Drive Tests (MDT); Overall description; Stage 2," Technical Specification (TS) 37.320, 3rd Generation Partnership Project (3GPP), 03 2017, Version 14.0.0.

[3] Yapeng Wang, Xu Yang, Yutian Zhao, Yue Liu, and Laurie Cuthbert, "Bluetooth positioning using rssi and triangulation methods," in *Consumer Communications and Networking Conference (CCNC), 2013 IEEE*. IEEE, 2013, pp. 837–842.

[4] Azin Arya, Philippe Godlewski, and Philippe Mellé, "Performance analysis of outdoor localization systems based on rss fingerprinting," in *Wireless Communication Systems, 2009. ISWCS 2009. 6th International Symposium on*. IEEE, 2009, pp. 378–382.

[5] Sinem Coleri Ergen, Huseyin Serhat Tetikol, Mehmet Kontik, Raffi Sevlian, Ram Rajagopal, and Pravin Varaiya, "Rssi-fingerprinting-based mobile phone localization with route constraints," *IEEE Transactions on Vehicular Technology*, vol. 63, no. 1, pp. 423–428, 2014.

[6] Elina Laitinen, Jukka Talvitie, Elena-Simona Lohan, and Markku Renfors, "Comparison of positioning accuracy of grid and path loss-based mobile positioning methods using received signal strengths," *CDROM Proc. of SPAMEC*, pp. 1–4, 2011.

[7] Roberto Battiti, Nhat Thang Le, and Alessandro Villani, "Location-aware computing: a neural network model for determining location in wireless lans," Tech. Rep., University of Trento, 2002.

[8] Siddhartha Saha, Kamalika Chaudhuri, Dheeraj Sanghi, and Pravin Bhagwat, "Location determination of a mobile device using ieee 802.11 b access point signals," in *Wireless Communications and Networking, 2003. WCNC 2003. 2003 IEEE*. IEEE, 2003, vol. 3, pp. 1987–1992.

[9] Shih-Hau Fang and Tsung-Nan Lin, "Indoor location system based on discriminant-adaptive neural network in ieee 802.11 environments," *IEEE Transactions on Neural networks*, vol. 19, no. 11, pp. 1973–1978, 2008.

[10] Wuri A Hapsari, Anil Umesh, Mikio Iwamura, Malgorzata Tomala, Bódog Gyula, and Benoist Sebire, "Minimization of drive tests solution in 3gpp," *IEEE Communications Magazine*, vol. 50, no. 6, pp. 28–36, 2012.

[11] 3GPP, "Telecommunication management; Subscriber and equipment trace; Trace control and configuration management," Technical Specification (TS) 32.422, 3rd Generation Partnership Project (3GPP), 09 2017, Version 15.0.0.

[12] 3GPP, "Evolved Universal Terrestrial Radio Access (E-UTRA); Physical layer; Measurements," Technical Specification (TS) 36.214, 3rd Generation Partnership Project (3GPP), 09 2017, Version 15.0.0.

[13] Jiangbo Zhu, Xinlong Luo, and De Chen, "Maximum likelihood scheme for fingerprinting positioning in lte system," in *Communication Technology (ICCT), 2012 IEEE 14th International Conference on*. IEEE, 2012, pp. 428–432.

[14] Jussi Turkka, Tuomas Hiltunen, Riaz Uddin Mondal, and Tapani Ristaniemi, "Performance evaluation of lte radio fingerprinting using field measurements," in *Wireless Communication Systems (ISWCS), 2015 International Symposium on*. IEEE, 2015, pp. 466–470.

[15] Tuomas Hiltunen, Jussi Turkka, Riaz Mondal, and Tapani Ristaniemi, "Performance evaluation of lte radio fingerprint positioning with timing advancing," in *Information, Communications and Signal Processing (ICICS), 2015 10th International Conference on*. IEEE, 2015, pp. 1–5.

[16] Quoc Duy Vo and Pradipta De, "A survey of fingerprint-based outdoor localization," *IEEE Communications Surveys & Tutorials*, vol. 18, no. 1, pp. 491–506, 2016.