A Floor Distinction Method Based on Recurrent Neural Network in Cellular Network

Yongliang Zhang[1,3], Lin Ma[1,3(✉)], Danyang Qin[2], and Miao Yu[3]

[1] School of Electronics and Information Engineering, Harbin Institute of Technology, Harbin, China
malin@hit.edu.cn
[2] School of Electronic Engineering, Heilongjiang University, Harbin, China
[3] Key Laboratory of Police Wireless Digital Communication, Ministry of Public Security, Harbin, China

Abstract. Indoor localization is nowadays becoming a hot topic and research trend for future large-scale location-aware services, particularly in high-rise buildings with complex structures. However, the indoor positioning methods existing are just with high interests of two-dimensional planar information, and the crucial height information for accurate position result is awfully neglected. Furthermore, without considering the shadow effect caused by indoor constant changing impact on the terminal to be located, positioning methods cannot achieve a desirable localization accuracy for building environment. In this paper, we proposed a fast and reliable method using deep neural network for floor-level distinction and position estimation based on ubiquitous radio waves in mobile communication system. The framework composed of autoencoder to extract the effective feature vectors and recurrent neural network classifier to solve the mis-classification caused by timing-discontinuity of received signal. It is shown that the accuracy of floor distinction is over 90.2% in different structural construction environments, which can provide comparable to current top-performing floor localization methods.

Keywords: Floor distinction · Autoencoder · Recurrent neural network · LTE

1 Introduction

By growing the demand for location-based services (LBS) in indoor environments, covering more detailed and multivariate information localization object is becoming the research interest at the present stage [1]. The emphasis of the solution is shifting from higher accuracy to more robust and lower costs, especially in 3D urban environment. One of the most popular and promising technology for indoor environment is fingerprint-based method, which uses received signal strengths (RSS) from installed wireless equipment to estimate users' location [2]. In general, cellular networks are usually not considered as a choice for indoor location due to its shadow attenuation and its uncontrollable environmental changes. However, with the widely covered by Long Term Evolution (LTE), this trend has been changing. The collaboration of macrocells

S. Han et al. (Eds.): AICON 2019, LNICST 287, pp. 380–392, 2019.
https://doi.org/10.1007/978-3-030-22971-9_33

and femtocells, which are placed in the signal blind zone, can achieve a satisfactory performance. Furthermore, LTE protocol defines specific reference signals and position protocols to support indoor location methods [3, 4].

Fingerprint-based methods usually include two steps, an offline step at which constructed databases by collecting signal parameter transmitted by APs and online step at which UEs are located by matching parameter values [5]. The fingerprint can be images, acoustic waves, visible light, radio signals, and other movement characteristics [6]. But with more and more high-rise buildings rising, the labor-intensive and time-consumed is becoming an important factor which confines the development of fingerprinting methods, especially in complex large-scale constructions. LTE system focus on combining both communication and localization capabilities, as well as location-based services. In LTE Positioning Protocol (LPP) Release 14, three main methods and some auxiliary methods are defined [3], and more attention spent on indoor positioning enhancement for the LTE standard. The large signal bandwidth in LTE enables positioning information real-time transmission for localization, and users can know where they located with not different about indoor and outdoor [7]. Theoretically, LTE coordinated networks can get a positioning accuracy about one meter ideally [8]. But propagation effects always be there, such as shadow and multipath. The deep neural network (DNN) can provide satisfactory results to classification due to its strong robustness and fault tolerance to a wide range of conditions. Positioning systems combined with DNN in various ways have been explored by researchers, especially in fields of time-varying and complex structure. Experimental results show that DNN-based positioning methods can get a state-of-art performance compared with fingerprinting methods [9]. Despite the merit, the mentioned methods are majority developed for 2D scenarios. Due to the serving devices mainly arranged in buildings, such as large shopping malls or school campus, there is a great increasing demand for the indoor location with height information.

One major challenge in LTE 3D indoor location is how to deal with the missing information caused by random fluctuation signals. In [10], a new inference system based on machine learning is proposed to estimate UEs location. The main point is the dealing method to the sparse received information and the median accuracy is 20 m for outdoor. Zhang. We proposed DNN system to generates a coarse positioning estimate and refined by a hidden Markov model [11]. [12] propose a Fingerprint-based Method Based Deep Extreme Learning Machine to extracted features for classification. Xuefeng Yin proposed a novel fingerprint-based localization technique which using physical layer parameters of cellular network to generate feature vector map and a feedforward neural network to estimate the position [13]. In [14], on the other hand, a DNN consisting of a stacked autoencoder (SAE) and a feedforward multi-class classifier is used for building/floor classification. In [15], the author investigates the possibility to use Channel State Information (CSI) extracted from LTE signals for fingerprinting localization both for indoor and outdoor. But it also ignores the difference between floors in the same building.

Considering the challenges, in this paper, we propose a new DNN architecture which combines Autoencoder (AE) to feature extraction from the noisy signal and Recurrent Neural Network (RNN) to deal with the reported data missing for complex floor environments based on LTE physical layer parameters. All parameters we used can be captured by UE's downlink signals of networks. The main contributions of our work are: (1) totally five signal parameters are considered to construct the feature matrix, especially the geo-information of base station is considered. (2) AE is utilized to reduce the feature space dimension and construct the feature matrix. And RNN is used to deal with data missing in complex buildings. (3) the localization framework we proposed considers different types of buildings, such as high-buildings and multi-buildings, mail areas and residences areas, etc.

The rest of the paper is structured as follows. In Sect. 2, we provide an overview of LTE systems and introduces relevant detail of terminologies. Section 3 presents a reliable framework for multi-floor indoor location in different scenarios. In Sect. 4, we show the results of the experiment to confirm the effects of the framework, and finally concludes our work and suggests areas of further research in Sect. 5.

2 Related Technical Background

2.1 Relevant LTE Technical Parameters

The Long Term Evolution (LTE) is an intermediate transitional mobile communication system from 3G to 4G. It inherits most of the standard from the Universal Mobile Telecommunication System (UMTS) to maintain backward compatibility. Moreover, three main methods and some auxiliary methods are defined for positioning. The fundamental cause of rapid promotion of location performance is signal bandwidth spread from 1.4 MHz to 20 MHz. And with that characteristics, we can take out physical layer parameters which cannot use for localization as location features in the 3G system. The parameters relevant for our work are list below.

Reference Signal Received Power (RSRP). It's one of the key parameters in LTE, which represents received signal strength in the wireless network. RSRP is total measured time averaged received signal power at UE from all downlink reference signals carried by a symbol. UE can receive several RSRP values from several transmitters, and it's also the main indicator of choosing the Serving Cell.

Reference Signal Received Quality (RSRQ). RSRQ refers to the quality of received reference signal. Its value ranged from –3 to –19.5, used as a criterion of Cell handover and re-choosing through ranking from largest to smallest.

Signal to Interference Plus Noise Ratio (SINR). In the LTE network, SINR means the ratio of useful received signal power and noise signal power and it also represents communication environment of the channel. Different from RSRQ, SINR puts emphasis on the decision of the size of the transmission data block, the encoding mode, and the modulation mode, etc.

E-UTRAN Cell Identifier (ECI). The ECI is a unique ID of a base station in Public Land Mobile Network (PLMN). Typically, an eNodeB represent by its ECI divided into 3 sectors with 120° to cover the whole area. And it's also the middle node to connect UE and Mobility Management Entity (MME).

Distance from eNodeB to UE (DENU). We choose the distance from UE to its connected eNodeBs as the fifth feature to detect how high the UE locates. Our hypothetical principle is that channels in cities between dense building areas and sparse building areas is two types of channel models, because the channel of high floor is less sheltered by the nearby building than that of low floor. UE in high floor spontaneously can own less shadow environment for its higher than some other architectures, such as buildings, bridges and towers, etc. As shown in Fig. 1, UE in high floor can get an almost direct signal, but UE in low floor get the signal from the same cell is weaker than high ones due to more shadows of buildings obstructing the propagation path.

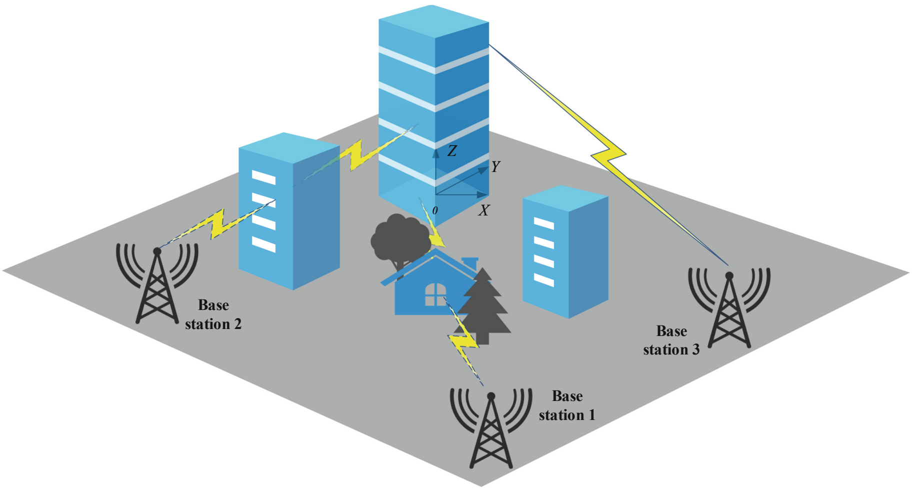

Fig. 1. Signal propagation paths of high floor and low floor.

2.2 The Principle of LTE Cell Selection

In the LTE network, during each call or accessing Internet of UE, there will be measurement data interchanges between terminals and data centers [16]. Measurement data concludes users experiments within the LTE system, and it also reflects the surrounding environments of users, such as natural factors and artificial factors. In our work, we pay more attention to the event that UE hand-off from one base station to another one. As above mentioned, UE locate on different floors have different signal propagation channels, which leads to a connected eNodeB change. Event-based eNodeB switching process is shown in Fig. 2.

The main point of handoff happens or not is when certain standards defined events occur. LTE technical specification defined several events to guide UE report of measurements. Few of our concerned events are as follows:

A1: Event A1 represent the signal quality of Serving Cell is better than the defined threshold (dBm), and it triggered at UE.
A2: Event A2 means signal quality is worse than the threshold.

A3: Event A3 is triggered when a same frequency Neighbor Cell signal quality is better than Serving Cell by certain threshold.
A4: Event A4 is triggered when a different frequency Neighbor Cell signal quality is better than Serving Cell by a certain threshold.

The events triggered mainly by UE measured data, primarily are RSRP, RSRQ and SINR. What information is record depends on UE's surrounding environment that can describe effective features. So, when an event happened in a special scenario, and ECI also can represent the scenario between UE and eNodeB. Geo-information now can get by compared measurement ECI and network parameter list from operators, and we can use the relative distances of them to another feature.

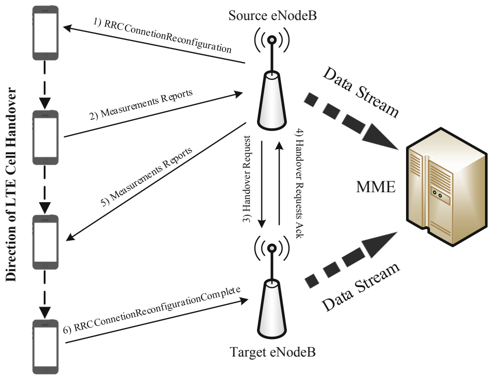

Fig. 2. The process of eNodeB handoff control

3 Proposed Floor Distinction Method

In this section, we mainly concentrate on the detail of designing the reliable neural network framework of floor detection. The framework consists of two parts: features refining and inevitable data missing.

3.1 Feature Parameter Matrix Construction

As mentioned above, we build the feature parameter matrix acquired through UE measurement report and a network parameter list. For measurement report data, we process as (1).

$$MRD_j = \begin{cases} MRD_j, & ECI_j \in \boldsymbol{ECI} \\ \xi, & ECI_j \notin \boldsymbol{ECI} \end{cases}, \quad j = 1, 2, \cdots, N \tag{1}$$

where ξ is a pre-set value vector, and ECI is the data set of all ECIs in the network parameter list. MRD is the data vector about received signal quality consist of RSRP, RSRQ and SINR. It constructs it as (2).

$$\mathbf{MRD} = \{RSRP_1,\ RSRQ_1,\ SINR_1,\ \cdots,\ RSRP_n,\ RSRQ_n,\ SINR_n\} \tag{2}$$

where n is the number of being "seen" ECI. So, the ξ is a vector including three factors standing for the default value of RSRP, RSRQ and SINR, which means at the place i UE cannot "see" the eNodeB$_i$. The measurement reports also recorded the phone's longitude and latitude data coordinating along with the timestamp for matching. Under the condition of known Longitude-Latitude information of both UE and eNodeB, the distance of them can be calculated as (3).

$$\begin{aligned} d_{1,2}^2 &= 2 \cdot [1 - \cos(lat1 - lat2) \\ &\quad + \cos(lat1) \cdot \cos(lat2) - \cos(lat1) \cdot \cos(lat2) \cdot \cos(lon1 - lon2)] \\ DENU &= 2R \cdot \arcsin\left(\frac{d_{1,2}}{2}\right) \end{aligned} \tag{3}$$

where the earth is seen as a sphere with radius R. $d_{1,2}$ is the linear distance between UE and base station. Finally, we can get a feature matrix with the floor number as (4).

$$\begin{aligned} F &= [MRD,\ ECI,\ DENU] \\ \mathbf{F} &= \begin{bmatrix} F_{11} & F_{12} & \cdots & F_{1N} \\ F_{21} & F_{22} & \cdots & F_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ F_{M1} & F_{M2} & \cdots & F_{MN} \end{bmatrix} \end{aligned} \tag{4}$$

where N is the total number of eNodeB, M is the number of measurement data with timestamp. But it needs to note that some row values of F are null because of internal or external factors, such as different system switching or sudden shade. So, a sparse feature matrix in rows and columns is produced for the next step at last.

3.2 Feature Matrix Refinement

For achieving an accurate positioning result in a 3D indoor environment, we choose 5 parameters as the features to train the network. But some of these parameters are not independent of others, which is harmful to our training network. For one hand, the non-independent parameters input the network for training will make network complexity increase sharply. For the other hand, training the non-independent parameter matrix can reduce the effectiveness of the network. To make better use of the parameters and achieve a satisfactory floor distinction result, we introduce AE to infer the ideal feature matrix from the observation data.

The aim of an autoencoder is to learn a representation (encoding) for a set of data, typically for dimensionality reduction, by training the network to ignore signal "noise." As shown in Fig. 3, x is the input data, and y is the "recovered" data which should be as close to x as possible. L(x, y) is the reconstruction error shown in (5), f_θ is transfer function from the input layer to hidden layer and g_θ is same as f_θ but from hidden layer to output layer.

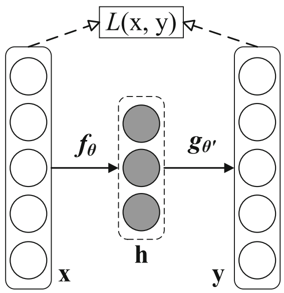

Fig. 3. Autoencoder

$$\arg\min_{\theta,\theta'} L(x,\ y) = \arg\min_{\theta,\theta'} L(x,\ g_{\theta'}(f_\theta(x))) \tag{5}$$

Autoencoder pursues training to replicate its input to its output. The encoding processing can be seen as a feature extraction for the size of the hidden layer is much smaller than the input layer in most cases. This structure forces the autoencoder to engage in dimensionality reduction and learn how to ignore noise to position accuracy.

3.3 Proposed Floor Distinction Method

The proposed localizer is an RNN network which consists of 4 layers. A recurrent neural network (RNN) is a class of artificial neural network where connections between nodes form a directed graph along a sequence. This allows it to exhibit temporal dynamic behavior for a time sequence. RNN can use their internal state (memory) to process sequences of inputs. This makes them applicable to tasks which have high linkages to the backward information and forward information. So, we use RNN to solve the floor distinction problem, as shown in Fig. 4.

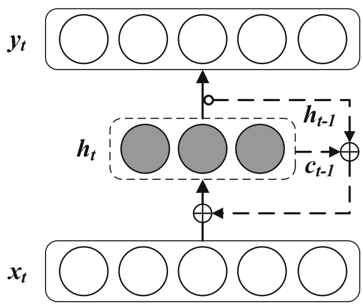

Fig. 4. Recurrent Neural Network

To better illustrate how RNN works, we unfold Figs. 4 to 5. $x^{(t)}$ is the input when the sequence index number is t. $h^{(t)}$ is the hidden state when the sequence index number is t. $o^{(t)}$ is the predicted output when the sequence index number is t. $L^{(t)}$ is the loss function. $y^{(t)}$ is the real output at when trains the sample. U, W and V are the weight matrixes which are to be optimized. We can get $h^{(t)}$ by

$$h^{(t)} = \sigma\left(z^{(t)}\right) = \sigma\left(Ux^{(t)} + Wh^{(t-1)} + b\right) \tag{6}$$

where σ is the *tanh* activation function.

$$o^{(t)} = Vh^{(t)} + c \tag{7}$$

Finally, we can get the estimated output when the sequence index number is t.

$$\hat{y}^{(t)} = \sigma'\left(o^{(t)}\right) \tag{8}$$

where σ' is the *softmax* activation function. And the loss function is defined as:

$$L = \sum_{t=1}^{\tau} L^{(t)} = \sum_{t=1}^{\tau} \left(\hat{y}^{(t)} - y(t)\right)^2 \tag{9}$$

where τ is the residence time in the network. The training phrases use back-propagation algorithm to achieve, which is same as the traditional neural network do.

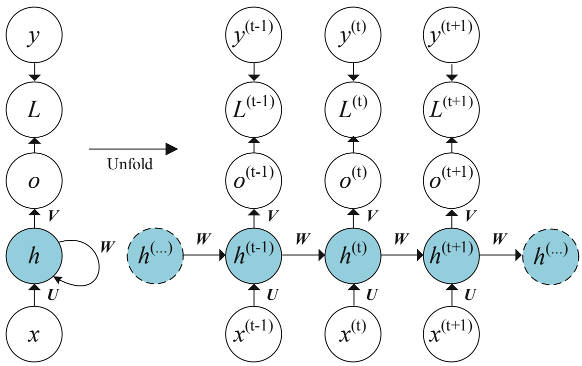

Fig. 5. The RNN unfolded by time

We put the first part of autoencoder which used for feature extraction and the second part of RNN which used for floor distinction together. In particular, the combined model is a network at least 4 layers which can depict the internal relationship between the feature matrix and UE locations. As shown in Fig. 6. Note that we can train the data of different buildings together or separated, but former lead to a rising time complexity to achieve the same accuracy.

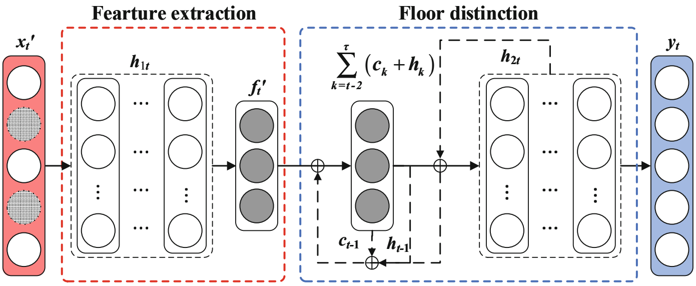

Fig. 6. The architecture of floor distinction based on AE and RNN

4 Experimental Results

In this section, we describe our experimental details and results using AE-RNN framework to confirm its validity in positioning accuracy in a 3D indoor environment. The experiments we chose are 4 different buildings including a teaching building, a shopping mall and two residential buildings. A professional network optimization software equipped with XiaoMi Note3 was recording measurement reports at every floor in all buildings. We extract 80% data randomly as the training and validation dataset, and the others as the testing dataset. We chose at least 4 points at each floor as the testing point and each point collects not less than 1000 piece of data for the consistency and completeness of dataset.

4.1 Data Processing

The original measurement report contained a lot of useless data and some useful but destroyed data should be clean out. Moreover, considering UE's maximum number of neighbor cell is six in TD-LTE network, we just kept the pieces of data containing the largest six RSRP values in the dataset and set other RSRP values ξ_{RSRP}. We set $\boldsymbol{\xi} = \{\xi_{RSRP}, \xi_{RSRQ}, \xi_{SINR}\}$ is a zero vector because the concrete value of ξ does not affect the final estimation results. After handling the received signal data, we added some geo-information to the dataset. Figure 7 shows the difference of distance from UE to eNodeBs, which measured from same buildings. Although distinguishing higher floors seems harder, there is a rule in distance of UE to eNodeB.

4.2 Model Generation

To verify the performance of the proposed framework, we construct the whole network with 2 hidden layers and the first hidden layer is the feature extraction layer. The output layer of RNN is a multi-label classifier, which the number of nodes equal to one-hot-encoded floor numbers. It makes easy to process for networks to further works. Network parameters in Table 1 summarize according to experimental results or determine a range to optimization.

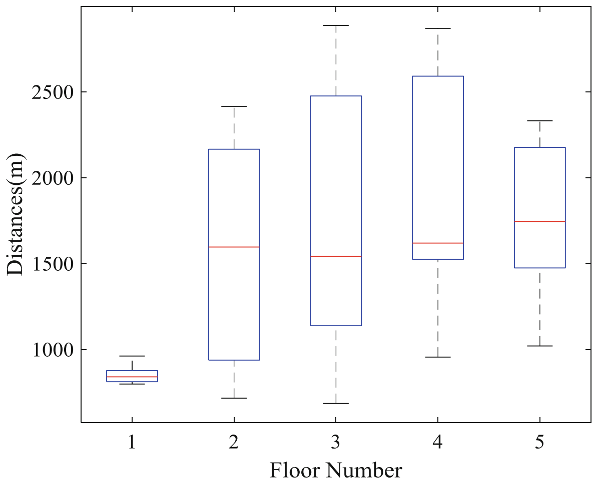

Fig. 7. Distance from UE to base stations

We pay our attention to the floor labels although the positioning accuracy can be further refined because 2D localization methods are sophisticated and perfect enough. In Table 1, the number of neurons C in feature refined layer is the high-light part for its direct influence on positioning accuracy. So, we set different values of C to find its trend for location, as shown in Fig. 8. We can note that when C = 100, the accuracy is tending towards stability, which means we can use 100 dimensions to express data of 784 dimensions in our work.

Table 1. Parameter values of the networks.

Network parameter	Value
Ratio of training data to overall data	80%
AE batch size	50
AE number pochs	784
AE feature layer size	100
RNN batch size	50
RNN number pochs	50
RNN input layer size	100
RNN output layer size	10

4.3 Floor Distinction Performance

In this section, we evaluate the floor distinction performance of our framework compared with fingerprint-based positioning method. In the fingerprint-based method, we choose KNN as the classifier and the K = 3. The training phase used random weight matrixes and bias, and we do not take the training phase in offline into account.

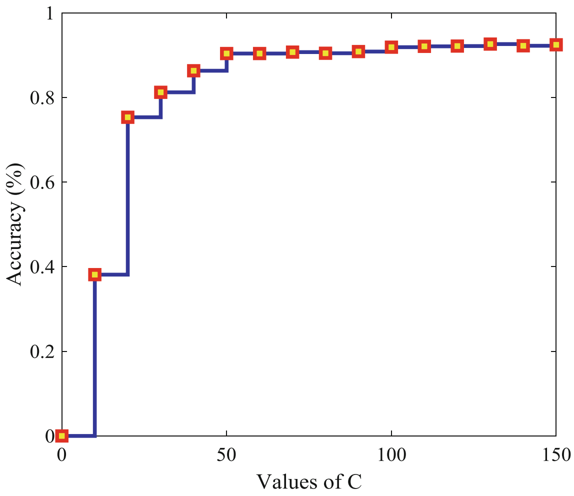

Fig. 8. The influence of value C to floor distinction accuracy

According to the results shown in Table 2, our framework can achieve the best estimation accuracy than others, the hit rate can get 91.28%, nearly 10% higher than traditional fingerprint-based positioning method. But the price is more time needed to position. The reason is RNN network needs to "remember" more information about some periods of time, more time retention in the network, more resources (time and space) consumed on it. In fact, KNN localizer aims to determine the floor position using the least time, but only for single-structured environments. When the environment become complex and unstable, such as human flow or temporary shadow, the method seems to be unreliable. As can be seen, our framework can improve the localization success rate and make the process more reliable. Also, adding extra training data can further affect the reliability of estimation considerably.

Table 2. Floor distinction success rate for different methods.

Method	Success rate (%)	Times (s)
Fingerprint-based	81.12	1.87
AE + RNN	91.28	18.39

5 Conclusions

In this article, we proposed a floor distinction framework consisted of Autoencoders and Recurrent Neural Network in complex environments. We utilize AE to reduce the feature space dimension and RNN, which is a memorable and associative network, to achieve a satisfactory floor distinction result. The proposed framework can not only extract the effective feature matrix from the measurement data which a huge impact on the size of network, but also distinct the number of floors precisely. Experimental results demonstrate that our models provide an efficient generalization performance in complex indoor environments. The framework is also addressed that it can solve the diversity of the positioning problems by modifying the network parameters in more readable manners. The framework can make an approving and reliable floor localization result in complex buildings. Furthermore, how to better use the relevance of the received data and eliminate the noise in the data forms an interesting work in future.

Acknowledgment. This paper is supported by National Natural Science Foundation of China (61571162, 61771186, 61701223); Ministry of Education-China Mobile Research Foundation (MCM20170106); Heilongjiang Province Natural Science Foundation (F2016019); University Nursing Program for Young Scholars with Creative Talents in Heilongjiang Province (UNPYSCT-2017125).

References

1. Filjar, R., Ševrović, M., Dadić, I.: Positioning and localization for Location-based services. In: 21st Telecommunications Forum Telfor (TELFOR), Belgrade, pp. 9–12 (2013)
2. Ma, L., Xu, Y.: Received signal strength recovery in green WLAN indoor positioning system using singular value thresholding. Sensors **15**(1), 1292–1311 (2015)
3. 3GPP Home Page. http://www.3GPP.org
4. del Peral-Rosado, J.A., et al.: Floor detection with indoor vertical positioning in LTE femtocell networks. In: IEEE Globecom Workshop, San Diego, pp. 1–6 (2015)
5. BASRI, C., El Khadimi, A.: Survey on indoor localization system and recent advances of WIFI fingerprinting technique. In: 5th International Conference on Multimedia Computing and Systems (ICMCS), Marrakech, pp. 253–259 (2016)
6. Vo, Q.D., De, P.: A survey of fingerprint-based outdoor localization. IEEE Commun. Surv. Tutor. **18**(1), 491–506 (2016)
7. Zekavat, R., Michael Buehrer, R.: Positioning in LTE. In: Handbook of Position Location: Theory, Practice and Advances, vol. 1, Wiley-IEEE Press (2012). Chapter 32
8. del Peral-Rosado, J.A., López-Salcedo, J.A., Zanier, F., Crisci, M.: Achievable localization accuracy of the positioning reference signal of 3GPP LTE. In: International Conference on Localization and GNSS, Starnberg, pp. 1–6 (2012)
9. Kim, K.S., Lee, S., Huang, K.: A scalable deep neural network architecture for multi-building and multi-floor indoor localization based on Wi-Fi fingerprinting. Big Data Analytics **3**(1), 4 (2018)
10. Ray, A., Deb, S., Monogioudis, P.: Localization of LTE measurement records with missing information. In: The 35th Annual IEEE International Conference on Computer Communications, IEEE INFOCOM 2016, San Francisco, pp. 1–9 (2016)
11. Zhang, W., Liu, K., Zhang, W., Zhang, Y., Gu, J.: Deep neural networks for wireless localization in indoor and outdoor environments. Neurocomputing **194**, 279–287 (2016)
12. Khatab, Z.E., Hajihoseini, A., Ghorashi, S.A.: A fingerprint method for indoor localization using autoencoder based deep extreme learning machine. IEEE Sens. Lett. **2**(1), 1–4 (2018)
13. Ye, X., Yin, X., Cai, X., Pérez Yuste, A., Xu, H.: Neural-network-assisted UE localization using radio-channel fingerprints in LTE networks. IEEE Access **5**, 12071–12087 (2017)
14. Nowicki, M., Wietrzykowski, J.: Low-effort place recognition with WiFi fingerprints using deep learning. In: Szewczyk, R., Zieliński, C., Kaliczyńska, M. (eds.) ICA 2017. AISC, vol. 550, pp. 575–584. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-54042-9_57

15. Pecoraro, G., Di Domenico, S., Cianca, E., De Sanctis, M.: LTE signal fingerprinting localization based on CSI. In: IEEE 13th International Conference on Wireless and Mobile Computing, Networking and Communication, Rome, pp. 1–8 (2017)
16. Sesia, S., Toufik, I., Baker, M.: LTE, The UMTS Long Term Evolution: From Theory to Practice. Wiley (2009)