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Wi-Fi fingerprinting-based floor detection using adaptive scaling and weighted autoencoder extreme learning machine

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ABSTRACT

In practical applications, accurate floor determination in multi-building/floor environments is particularly useful and plays an increasingly crucial role in the performance of location-based services. An accurate and robust building and floor detection can reduce the location search space and ameliorate the positioning and wayfinding accuracy. As an efficient solution, this paper proposes a floor identification method that exploits statistical properties of wireless access point propagated signals to exponent received signal strength (RSS) in the radio map. Then, using single-layer extreme learning machine-weighted autoencoder (ELM-WAE) main feature extraction and dimensional reduction is implemented. Finally, ELM based classifier is trained over a new feature space to determine floor level. For the efficiency evaluation of our proposed model, we utilized three different datasets captured in the real scenarios. The evaluation result shows that the proposed model can achieve state-of-art performance and improve the accuracy of floor detection compared with multiple recent techniques. In this way, the floor level can be identified with 97.30%, 95.32%, and 96.39% on UJIIndoorLoc, Tampere, and UTSIndoorLoc datasets, respectively.

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1. INTRODUCTION

The popularity of smart mobile devices and their ubiquitous use in daily life especially indoors has provided many location-based services such as emergency relief and rescue, location-based information arrival, marketing, advertisement, indoor wayfinding, and navigation. Awareness of location is a key prerequisite for providing these services [1]–[3]. In outdoor environments, global navigation satellite systems (GNSS) provide precise geospatial positioning. Due to attenuation of the received signal strength (RSS) either caused by missing the line-of-sight (LOS) between the satellite and user and also multipath effects, this technology does not carry out well indoors. Location estimation in huge multi-floor/store buildings is more challenging. In these complex environments, accurate floor identification as a prerequisite for success in providing these services is crucial. For example, in an emergency condition (e.g., fire in a multi-floor building), accurate floor identification is more crucial for the first responders. Although many studies have leaned towards positioning in two dimensions on a single floor, accurate floor identification, as a key prerequisite for indoor positioning and success in providing these services remains a big challenge. Current floor identification approaches exploit three techniques including wireless local area network (WLAN) technologies, inertial/pressure-based systems, and hybrid methods. Among these, motion detection-based systems, which utilize the inertial measurement unit (IMU) in addition to the magnetic field and/or the barometer are particularly susceptible to noise and suffer from deviation over time, and need to initialize and calibrate. Furthermore, they are not available on all devices; which limits the efficiency of these types of systems. Again, due to the ubiquitous deployment and cost-effectiveness of Wi-Fi technology in indoor environments, Wi-Fi-fingerprinting-based location estimation has attracted much attention in recent years [4]–[6].

The fingerprinting method is conducted in two separate phases. At first, the entire indoor space is divided into grid points, and the center of each grid is considered as an individual reference point (RP). Then, in the offline phase thru an operation named *the survey process*, the received signal strength (RSS) fingerprints from detected media access control (MAC) addresses in each RP are collected. Then, the RSS along with location information of each fingerprint are saved in a dataset known as a radio map. During the online phase, a pattern matching/learning algorithm compares the current Wi-Fi measurement with the radio map database to capture the information of the target location. This mechanism is shown in Figure 1.

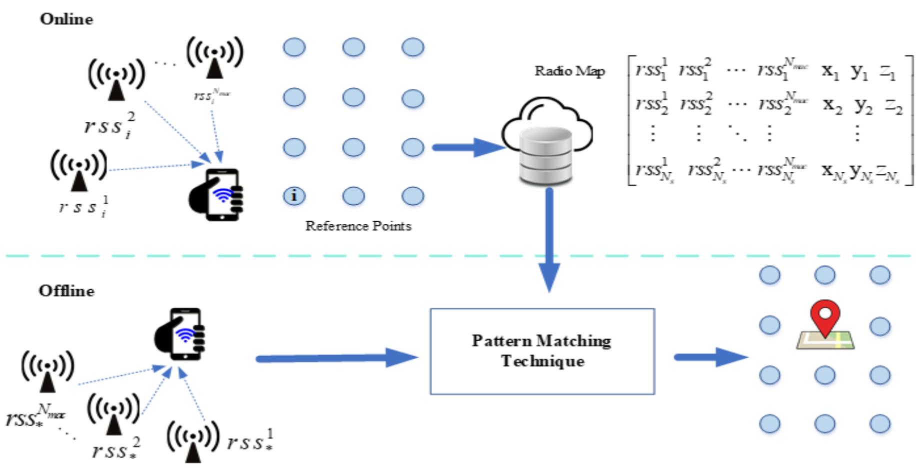

Figure 1. Wi-Fi fingerprinting based positioning process

In practice, the following challenges related to Wi-Fi fingerprinting schemes must be handled to achieve the desired efficiency. i) The multipath effect is caused by non-line-of-sight (NLOS) propagation due to the presence of static and mobile obstacles between transmitter and user which lead to unstable RSS readings. ii) Device heterogeneity in both online and offline phases has a significant impact on the accuracy of position identification. Recently, the trend towards deep learning has been increased. Due to less parameter tuning, automatic feature extraction, and good scalability in complex indoor environments, deep learning-based procedures can achieve desirable solutions for fingerprint-based positioning [7]–[10]. The positioning accuracy of these schemes depends on network depth, and by increasing the number of layers, their fine-tuning process can be time-consuming, and computational complexity increases.

To address this problem, an extreme learning machine (ELM) and autoencoder-based ELM as a novel fast supervised and unsupervised learning technique, are employed in [11]. ELM does not need the iterative backpropagation process to fine-tune the weights, which leads to significant training time reduction and as an efficient classifier has been successfully exploited in many applications [12]–[14]. In this study, we use an extreme learning machine based weighted autoencoder to extract key features of Wi-Fi data. Then, to identify the floor, we train an extreme learning machine-based classifier. In addition, we have proposed a new scaling mechanism to overcome the effect of device heterogeneity on the received signal strength. The main contribution of this paper can be summarized:

a. Due to the need to deal with the device diversity influence and signal fluctuations, we proposed a new representation of Wi-Fi data instead of raw data or normalized ones. We proposed the usage of novel access point adaptive exponential data for feature extraction and classifier training.
b. We exploit single layer ELM-based weighted autoencoder for key feature extraction and input dimensional reduction. Then, we train ELM with new extracted features of the training set.
c. We evaluate the performance of the proposed method on available three different datasets; UJIIndoorLoc (IPIN-2015 competition) [15], UTSIndoorLoc [16], and Tampere [17]. The training process in each testbed is done separately, and the experimental results demonstrate that our simple proposed scheme outperforms the state-of-the-art approaches on floor-level prediction.

The rest of this paper is organized: The relevant literature on floor positioning is described in section 2. The preliminaries including ELM theory and ELM-AE can be found in section 3. The proposed method is explained in section 4. The performance evaluation on different testbeds and experiment results are demonstrated in section 5, and finally, section 6 concludes this paper.

2. RELATED WORKS

With the growing popularity of smart mobile devices such as smartphones, tablets, and smartwatches, the need for cost-effective choices in providing location-based service is also felt more than ever [18]. Floor level determination using sensors embedded in a smart device can be divided into four categories: wireless signal based techniques (e.g. Wi-Fi and Bluetooth) [19]–[21], inertial measurement unit based systems (IMU, Magnetic Field) [22]–[24], barometric pressure-based methods and hybrid ones [25]–[27]. In this study, we focus on Wi-Fi based methods in multi-building/floor environments both for floor and coordinate estimation.

The TrueStory system proposed in [19] consists of several weak learners. Floor level detection is implemented using Wi-Fi connectivity information and access point location. It utilizes a multilayer perceptron neural network to combine floor classifier learners. However, the results are not very satisfactory for complex environments. An access point and building-independent floor detection method, titled StoryTeller, is proposed in [20]. The authors harness generated images using Wi-Fi signals to train the convolutional neural network. Although this system is calibration-free and can be applied to any building, it does not have acceptable accuracy in complex environments with heterogeneous devices.

ZeeFi system, based on deep learning, is proposed in [21]. After fingerprint construction using two smartphone measurements as GNSS, Wi-Fi, barometer, the light sensor in a crowdsourcing approach, they used two-layer stacked autoencoders with 500 and 200 units to determine the floor level based on only Wi-Fi measurements. ZeeFi system can achieve 98% accuracy in terms of floor identification with 3% better performance than k-nearest neighbors (KNN). However, there has been no significant improvement over the simple KNN method. In [23], a magnetic field fingerprint relative to smartphone attitude was utilized to determine the floor level in a multi-floor building. Due to improved accuracy of floor detection, they were able to employ three different classifiers to discriminate user’s walking activity on both stairs and plain surface based on gyroscope and accelerometer data. The foot-mounted IMU-based altitude estimation is studied in [24]. To recognize vertical changes including upstairs, downstairs, and horizontal movements, they exploited the adaptive network-based fuzzy inference system.

In [25], a hybrid floor level detection method is proposed which utilizes Wi-Fi signals and a barometer on a floor. The authors exploit floor information obtained from Wi-Fi data to calibrate barometer pressure-based floor detection. Another system that utilized barometric pressure data fused with Wi-Fi to determine the floor level is proposed in [26]. They used XGBoost to detect floor switching based on gyroscope and accelerometer signals. The authors combine the Wi-Fi-based floor positioning with the barometric pressure-based floor positioning results using the hidden Markov model. The proposed framework in [27], involves two steps, namely RSS processing using Monte Carlo Bayesian inference followed by fusion of barometric pressure and Wi-Fi using a Kalman Filter technique. Although it has good accuracy, its computational complexity is relatively high. The authors in [28] utilized the hierarchical essence of the building/floor/coordinates prediction and obtained an accuracy of 91.18% for floor detection on the UJIIndoorLoc dataset. In [16], a classification-based one-dimensional convolutional neural network (CNN) is incorporated with the feature extraction phase using stacked autoencoder (SAE). CNN based indoor localization system with WiFi fingerprints for multi-building and multifloor localization (CNNLoc) was able to perform positioning tasks with 96.03% accuracy in terms of floor detection on UJIIndoorLoc dataset.

The proposed system in [8] is based on a deep neural network. The extracted importance features using stacked denoising autoencoder is exploited to reconstruct radio map. They achieved 94.60% accuracy on the UJIIndoorLoc dataset. In [29], a semi-supervised deep extreme learning machine for two-dimensional positioning is proposed to ameliorate the classification accuracy with the help of unlabeled data. Due to the calculation of the Laplacian matrix, the time consumption of their method is high. The deep structure of ELM for two-dimensional positioning is proposed in [14]. They train our proposed network with normalized data after high level feature extraction by autoencoder. The constraint online sequential extreme learning machine (COSELM) classifier is proposed [30]. They exploited KNN and weighted sparse representation classification for Wi-Fi-based positioning, and 95.4% floor hit rate is obtained for floor detection on UJIIndoorLoc dataset. In [31], we utilized two layers ELM-sparse-autoencoder for feature extraction of raw RSS of radio map. We then exploited a single-layer ELM for floor classification.

In this paper, we propose an approach capable of handling device heterogeneity and signal attenuation that improves floor detection accuracy using Wi-Fi signals in complex multi-floor environments.

3. PRELIMINARIES

In this section, we will briefly review the ELM and ELM-AE theory.

3.1. ELM theory

An ELM is a single hidden layer feedforward network (SLFN) where hidden-node parameters are adjusted randomly and the output weights are analytically determined. Given N_s d-dimensional samples $\{\boldsymbol{X}\} \in \Re^{N_s \times d}$ along with their targets $\{\boldsymbol{T}\} \in \Re^{N_s \times d}$, ELM theory aims to minimize the error between training target and network output ($\boldsymbol{H\beta}$), and obtains the smallest norm of output weights ($\boldsymbol{\beta}$) [11]:

$$L_{elm} = \underset{\beta}{\operatorname{argmin}} \frac{C}{2} \|\boldsymbol{H\beta} - \boldsymbol{T}\|_2^2 + \frac{1}{2} \|\boldsymbol{\beta}\|_2^2, \qquad \boldsymbol{H} = \left[\boldsymbol{h}(\boldsymbol{x_1}), \ldots, \boldsymbol{h}(\boldsymbol{x}_{N_s})\right]^{\boldsymbol{T}} \in \Re^{N_s \times N_h}$$

$$\boldsymbol{h}(\boldsymbol{x_i}) = \left[\boldsymbol{g}(\boldsymbol{x_i}, \boldsymbol{w}_1, b_1), \ldots, \boldsymbol{g}(\boldsymbol{x}_{N_h}, \boldsymbol{w}_{N_h}, b_{N_h})\right]^{\boldsymbol{T}} \in \Re^{1 \times N_h}, \ \boldsymbol{\beta} \in \Re^{N_h \times N_c} \tag{1}$$

Where the number of hidden neurons is denoted with N_h. The $\boldsymbol{h}(\boldsymbol{x_i})$ indicates the output of hidden neurons for i-th input sample. $w_j, j = 1{:}\,N_h$ is the input weight vector connecting the input layer to the j-th hidden neuron, b_j is the bias weight of the j-th hidden neuron, and $g(.)$ denotes the activation function of the hidden layer. Then, by setting the gradient of (1) -with respect to $\boldsymbol{\beta}$- to zero, calculation of least square solution with smallest-norm can be summarized:

$$\boldsymbol{\beta} = \boldsymbol{H}^{\dagger}\boldsymbol{T} = \begin{cases} (\boldsymbol{H^T H} + \frac{I}{C})^{-1}\, \boldsymbol{H^T T} & N_s > N_h \\ \boldsymbol{H^T}(\boldsymbol{HH^T} + \frac{I}{C})^{-1}\, \boldsymbol{T} & N_s < N_h \end{cases} \tag{2}$$

3.2. ELM-AE

The main goal of extreme learning machine-based auto-encoder (ELM-AE) is to learn new meaningful data representation. Different from ELM classifier, ELM-AE aims to minimize the reconstruction error of input data. In this way, the loss function of ELM-AE can be formulated [32]:

$$L_{elm-ae} = \underset{\boldsymbol{\beta}_{ae}}{\operatorname{argmin}} \frac{1}{2} \|\boldsymbol{H\beta}_{ae} - \boldsymbol{X}\|_2^2 + \frac{1}{2} \|\boldsymbol{\beta}_{ae}\|_2^2 \tag{3}$$

The output weights $\boldsymbol{\beta}_{ae}$ can be calculated similarly to the ELM method mentioned earlier,

4. PROPOSED SYSTEM

In this section, the proposed scheme is presented. We first explain the data preparation and proposed representation process. Then, we introduce the detailed model design for building/ floor detection simultaneously using ELM-WAE.

4.1. Access point adaptive data scaling

Let us assume that the received signal strength of j-th access point in i-th reference point is indicated with $rss_{i,r}^j$. Our proposed data preparation process consists of three steps:

a. Convert RSSs to non-negative values

$$rss_{i,p}^j = rss_{i,r}^j - min \tag{4}$$

The lowest RSS value considering RSSs of radio map is indicated with min parameter.

b. Min-max normalization of non-negative RSSs of each reference point

$$rss_{i,n}^j = \frac{rss_{i,p}^j - \min(rss_p^j)}{\max(rss_p^j) - \min(rss_p^j)} \tag{5}$$

c. Exponentiation of min-max normalized data according to the statistical characteristics of each access point in the radio map.

$$rss_i^j = (rss_{i,n}^j)^{\beta_j} \tag{6}$$

Following the result reported in [26], how Wi-Fi data is displayed affects the positioning accuracy rate. The authors indicated that powered representation of RSS (6) is more effective than linear and exponential representations. The α is set to a constant value of e.

$$Powed_i = \left(\frac{rss_{i,p}^{j} - min}{-min}\right)^{\alpha} \tag{7}$$

In this study rather than a constant value, we set β_j according to statistical characteristics of each access point. We formulate it based on the confidence interval rule:

$$\beta_j = (\mu_j - 2\sigma_j/\sqrt{n_j})^{-1} \tag{8}$$

μ_j , σ_j are average and standard deviation of RSS received from j-th access point in radio map, respectively. The number of times the j-th access point is heard is indicated by n_j. These parameters can be calculated from training data in the offline phase. As indicated in Table 1, as a consequence of this scaling, RSS values received from the access point with a higher confidence interval are less penalized. The classification results show that by using our proposed data representation, the RSS space can be better separated and described more realistically.

Table 1. Transformed raw RSSs of five access points in accordance to (6) with $\beta = 1$ and the proposed scaling function

Raw (dBm)	$\beta = 1$	$\beta_j = (\mu_j - 2\sigma_j/\sqrt{n_j})^{-1}$	μ_j	σ_j	n_j
-90	0.28	0.12	0.6	0.24	4750
-61	0.93	0.88			
-77	0.67	0.51			
-90	0.31	0.06	0.43	0.2	4673
-61	0.89	0.76			
-77	0.45	0.15			
-90	0.24	0.11	0.66	0.24	2073
-60	0.95	0.92			
-77	0.65	0.51			
-90	0.24	0.02	0.39	0.20	1278
-61	0.82	0.59			
-77	0.62	0.28			
-61	0.74	0.54	0.50	0.23	798
-77	0.50	0.24			
-90	0.33	0.10			

4.2. Classification using ELM-WAE

Our proposed floor detection approach has two separate feature extraction and features classification phases. A detailed explanation of these two phases is provided:

A. Feature encoding with ELM-WAE

Let us assume that the radio map consists of N_s samples and N_{mac}detected access points. $\mathbf{\Phi}$, is represented by the following format where, rss_i^j, represents the signal strength of the j-th access point on the i-th reference.

$$\mathbf{\Phi} = \begin{bmatrix} rss_1^1 & rss_1^2 & \dots & rss_1^{N_{mac}} \\ rss_1^2 & rss_1^2 & \dots & rss_2^{N_{mac}} \\ \vdots & \vdots & \ddots & \vdots \\ rss_1^2 & rss_1^2 & \dots & rss_{N_s}^{N_{mac}} \end{bmatrix} \tag{9}$$

According to (3), the feature extraction with dimension reduction can be formulated:

$$L_{ae} = \underset{\boldsymbol{\beta}_{ae}}{\operatorname{argmin}} \frac{\boldsymbol{D}}{2} \|\boldsymbol{H}\boldsymbol{\beta}_{ae} - \mathbf{\Phi}\|_2^2 + \frac{c_{ae}}{2} \|\boldsymbol{\beta}_{ae}\|_2^2 \tag{10}$$

$\boldsymbol{D}$ and c_{ae} are balancing weights and regularization parameters, respectively. where $\boldsymbol{D}$ is an $N_s \times N_s$ diagonal matrix and their diagonal elements are the weights assigned to the training samples [11]. In this study we use the following weights:

$$\boldsymbol{D} = diag(D_{ii}),\ \ D_{ii} = \frac{1}{N_{f_i}} \tag{11}$$

Where N_{f_i} is the number of samples belonging to the floor of i-th sample. The optimized output weight matrix, $\boldsymbol{\beta}_{ae}$, is given by equating the derivative of the L_{ae} -with respect to $\boldsymbol{\beta}_{ae}$- to zero:

$$\boldsymbol{\beta}_{ae} = (\boldsymbol{H}^{\boldsymbol{T}}\boldsymbol{D}\boldsymbol{H} + c_{ae}\mathbf{I})^{-1}\ \boldsymbol{H}^{\boldsymbol{T}}\boldsymbol{D}\boldsymbol{\Phi} \qquad \boldsymbol{I} \in \Re^{N_h^{ae} \times N_h^{ae}} \tag{12}$$

Then, according to [32] the new data representation can be obtained:

$$\boldsymbol{\Phi}_{new} = g(\boldsymbol{\Phi}\boldsymbol{\beta}_{ae}^{\boldsymbol{T}}) \ \in \Re^{N_s \times N_h^{ae}} \tag{13}$$

Where g(.) is the activation function. In this study that for simplicity, $\boldsymbol{\Phi}_{new} = \boldsymbol{\Phi}\boldsymbol{\beta}_{ae}^{\boldsymbol{T}}$ is used. The proposed process follows in Algorithm 1.

Algorithm 1: ELM-WAE
Input: Scaled radio map $\boldsymbol{\Phi} \in \Re^{N_s \times N_{mac}}$, Target matrix $\mathbf{T} \in \Re^{N_s \times N_C}$, and c_{ae}
Output: Optimal autoencoder weight, $\boldsymbol{\beta}_{ae}^{\boldsymbol{T}} \in \Re^{N_{mac} \times N_{ae}}$ and new data representation $\boldsymbol{\Phi}_{new} \in \Re^{N_s \times N_{ae}}$
Training Steps:
1. Random assignment of input weights and biases $\{\boldsymbol{W}_{rnd}^{ae}, \boldsymbol{b}\}$
2. Weight Determination (10) $\boldsymbol{D} = diag(D_{ii}) \in \Re^{N_s \times N_s}$
3. Hidden layer output matrix calculation,
$[\boldsymbol{H}, .] = mapminmax(\ \boldsymbol{\Phi} \times \{\boldsymbol{W}_{rnd}^{ae}, \boldsymbol{b}\}, [0,1]) \in \Re^{N_s \times N_{ae}}$
4. Optimal output weight estimation
$\boldsymbol{\beta}_{ae} = (\boldsymbol{H}^{\boldsymbol{T}}\boldsymbol{D}\boldsymbol{H} + c_{ae}\mathbf{I})^{-1}\ \boldsymbol{H}^{\boldsymbol{T}}\boldsymbol{D}\boldsymbol{\Phi}$
5. Calculation of new data $\boldsymbol{\Phi}_{new} = \boldsymbol{\Phi}\boldsymbol{\beta}_{ae}^{\boldsymbol{T}}$

Test Step:
Input: Scaled test data $\boldsymbol{X}^{tst} \in \Re^{N_{tst} \times N_{mac}}$, $\boldsymbol{\beta}_{ae}$
Output: New test data $\boldsymbol{X}_{new}^{tst}$
1. Calculate new test representation
$\boldsymbol{X}_{new}^{tst} = \boldsymbol{X}^{tst} \times \boldsymbol{\beta}_{ae}^{\boldsymbol{T}} \in \Re^{N_{tst} \times N_{ae}}$
$\boldsymbol{X}_{new}^{tst} = mapminmax(\,.\,, \boldsymbol{X}_{new}^{tst}\,, .)$

B. Supervised classification with ELM

The ELM classifier is trained with training data with new feature space, $\boldsymbol{\Phi}_{new}$, similar to Section 3.1. Then, in the test phase, the class of each real-time RSS instance can be specified by applying an *argmax*(.) function to the classifier output. This process is summarized in Algorithm 2. The ELM-AE and ELM-classifier structures utilized in this study are depicted in Figure 2.

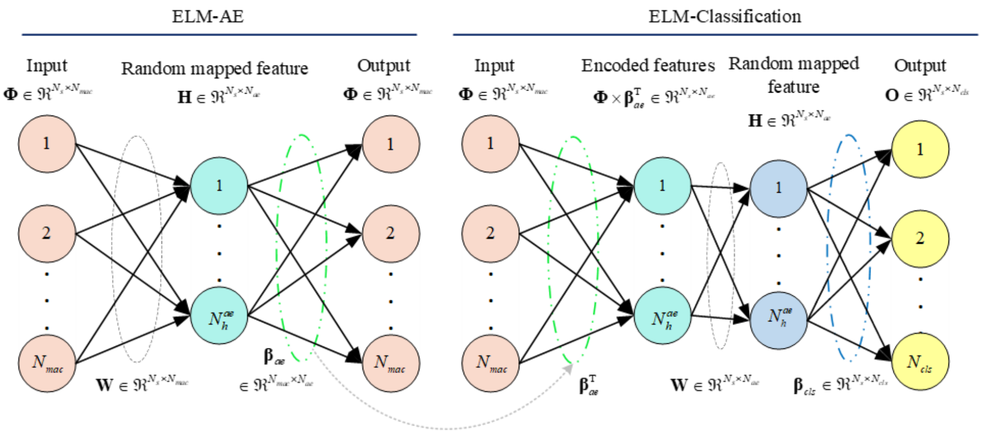

Figure 2. ELM-AE and ELM-classifier structures utilized in this study (For simplicity, biases are ignored in this figure)

Algorithm 2: ELM-Classification
Input: $\mathbf{\Phi}_{new} \in \Re^{N_s \times N_{ae}}$, c_{cls}
Output: $\boldsymbol{\beta}_{cls} \in \Re^{N_{ae} \times N_C}$
Training Steps:
1. Random assignment of weights and biases $\{\boldsymbol{W}_{rnd}^{cls}, \boldsymbol{b}\}$
2. Hidden layer output matrix calculation
$H = logsigmoid(\mathbf{\Phi}_{new} \times \{\boldsymbol{W}_{rnd}^{cls}, \boldsymbol{b}\})$
3. Optimal output weight estimation, $\boldsymbol{\beta}_{cls}$, as (2)
Test Step:
Input: $\boldsymbol{X}_{new}^{tst}$, $\boldsymbol{\beta}_{cls}$
Output: Estimated label of $\boldsymbol{X}_{new}^{tst}$
1. Random Hidden layer output calculation
$H = logsigmoid(\boldsymbol{X}_{new}^{tst} \times \{\boldsymbol{W}_{rnd}^{cls}, \boldsymbol{b}\}) \in \Re^{N_{tst} \times N_{ae}}$
2. Label determination $Lable = argmax(\boldsymbol{H} \times \boldsymbol{\beta}_{cls})$

5. PERFORMANCE EVALUATION

In this section, we evaluate the performance of the proposed floor detection method. At first, we describe our selected testbeds and parameters. Then, we evaluate the accuracy of our solution by comparing it with multiple approaches.

5.1. Data description and model adjustment

We used three different datasets to evaluate the performance or our proposed model. The UJIIndoorLoc Wi-Fi fingerprinting dataset is collected in three 4-5 floor buildings from 933 reference points, and with different Android devices and users. The database is divided into two training and test parts, which are collected four months apart [15]. The introduced UTSIndoorLoc data set in [16], was collected in 1840 locations on the 18-floor FEIT Building at Sydney University of Technology. The last used dataset, Tampere, is crowdsourced [17] collected from 4651 locations with 21 mobile devices in 5-floors of Tampere university (TU) building, Finland. The main features and details of these three datasets are compared in Table 2.

Table 2. Three different dataset features (include of five separate buildings)

Features	UJIIndoorLoc			Tampere	UTS
Building ID	Building 0	Building 1	Building 2	Building 3	Building 4
Number of floors	4	4	5	5	16
Number of train RPs	259	265	409	697	1466
Number of train samples	5249	5196	9492	697	9108
Number of test RPs	536	307	268	3951	388
Number of whole Aps	520	520	520	992	589

In the proposed model generation, there are four tuning parameters, i.e., the number of hidden nodes of the classification layer, regularization parameters, and the number of hidden nodes of the autoencoder layer. We adjusted these parameters in a hierarchical process somewhat similar to [11].

First, assuming $c_{cls} = 0.01$ and regardless of the encoder layers, we compute the accuracy of the ELM classifier for the various number of neurons in the range of [100:50:400]. Table 3, shows the results of our experiments in three datasets. As a good trade-off between accuracy and computational cost, we choose 300 and 200 values for (UJIIndoorLoc, UTS), and TU datasets. Since the value of the parameter, c_{ae}, does not have much effect in our experiments, we set it to 0.001, where reaches an acceptable amount of accuracy. Then, to adjust the number of autoencoder neurons, simultaneously with the change of the classification parameter in the range of 0.1 to 10^{-7}, we change the number of neurons in the range of [20:10:100], evaluating the model's accuracy. The accuracy of obtained models on the UJIIndoorLoc training dataset is reported in Table 4. According to the obtained results, 60 neurons with a generalization parameter equal to 10^{-6} is a desirable trade-off between accuracy and computational cost. This process was performed in two other datasets and the adjusted parameters are summarized in Table 5. In the UJIIndoorLoc consist of the three-building dataset with respective (4, 4, 5) floors, each row of the target matrix, $\mathbf{T}$, that indicates sample label, is adjusted as a 13-dimensional vector consisting of {1, -1}. This way, for example, if the seventh element is equal to one, it means that the sample belongs to the third floor of the second building.

Table 3. Comparison of training accuracy of ELM in terms of different neuron numbers ($c_{cls} = 0.01$)

Neuron Numbers	Accuracy (%)		
	UJIIndoorLoc	Tampere	UTSIndoorLoc
100	86.31	85.06	89.47
150	93.46	91.81	96.76
200	96.86	95.67	97.27
300	97.62	95.91	98.89
350	98.17	95.96	99.59
400	98.38	96.70	99.48

Table 4. Comparison of training accuracy of the proposed model in terms of different neuron numbers along with the change of c_{cls} on UJIIndoorLoc training dataset, ($c_{ae} = 0.001$)

Autoencoder Neuron Numbers	Accuracy (%) Classifier regularization parameter, c_{cls}						
	10^{-1}	10^{-2}	10^{-3}	10^{-4}	10^{-5}	10^{-6}	10^{-7}
20	74.19	75.52	77.31	85.67	92.180	97.34	98.21
30	86.47	86.71	87.70	91.16	96.24	98.50	98.96
40	90.79	90.99	91.88	95.57	98.06	98.76	99.01
50	92.69	93.29	94.70	97.48	98.64	98.86	99.06
60	95.21	95.53	96.81	98.07	98.90	99.25	99.22
70	96.22	96.63	97.36	98.43	99.09	99.19	99.24
80	96.51	97.08	97.71	98.56	99.14	99.17	99.17
90	97.28	97.48	97.94	98.77	99.15	99.23	99.24
100	97.42	97.57	98.05	98.88	99.21	99.29	99.29

Table 5. Training parameters of autoencoder and classifier tuned in three datasets

Paremeters	UJIIndoorLoc	Tampere	UTSIndoorLoc
Number of autoencoders hidden neurons	60	90	90
Number of Classifier hidden neurons	300	200	300
Autoencoder regularization parameter, c_{ae}	10^{-3}	10^{-3}	10^{-3}
Classifier regularization parameter, c_{cls}	10^{-6}	10^{-5}	10^{-6}
Activation function	sigmoid	sigmoid	sigmoid

5.2. Classification performance

We first evaluate the impact of the new data scaling on ELM performance without autoencoder layer applying. We evaluated the classification performance separately on the three buildings in the UJIIndoorLoc dataset increasing the number of hidden layer neurons from 100 to 2,000. The optimal regularization parameter is set to 0.001. Simulation results for two proposed scales and $\beta = 1$ (equal with min-max normalization) are illustrated in Figure 3. The simulation results confirm that the representation of the RSS data in the proposed method is independent of the hidden neuron numbers which improve classification accuracy. The highest accuracy is related to the use of the proposed scale, per 1000, 900, 500, and 2000 neurons, with 95.76%, 96.26%, 94.11% accuracy respectively on building 2, building 1, and building 0 (2.8%, 4.03%, and 7.016% better than $\beta = 1$ in same neurons).

The efficiency of our proposed ELM-WAE-based approach on the three testbeds and for different scales is compared in Table 6. We utilized $\beta = 1, e$, proposed, and powed scale (7) proposed in [33]. The results show that the proposed ELM-WAE-based classification with a new scale can achieve 98.32, 97.04, 95.89, 95.32, and 96.39 percentage accuracy in floor localization on five buildings, respectively that are better than other scale performances.

The confusion matrix of testing data in the UJIIndoorloc dataset is presented in Table 7. As shown, all three buildings are identified without error and only one case has a two-floor error (in the third building) and the rest have a single-floor detection error. We evaluate the performance of the proposed floor/building detection scheme by comparing it with the state-of-the-art methods on the three mentioned datasets.

Table 6. Comparison of floor success rate on five buildings in terms of different scales-based ELM-WAE

Scaling factor	Floor hit rate (%)				
	Building 0	Building 1	Building 2	Building 3	Building 4
$\beta = 1$	97.01	89.18	94.03	94.51	94.33
$\beta = e$	97.76	94.13	95.52	94.43	94.07
Powed (7)	98.13	95.11	95.14	94.46	94.85
$\beta = (\mu_j - 2\sigma_j/\sqrt{n_j})^{-1}$	98.32	97.05	95.89	95.32	96.39

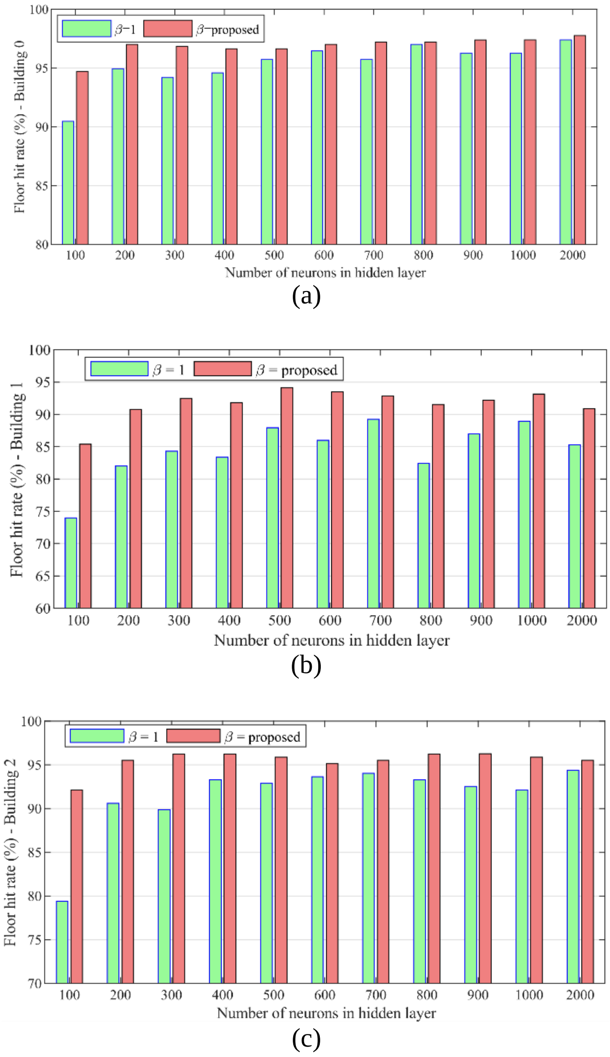

Figure 3. Comparison of ELM accuracy based two proposed scale and $\beta = 1$ on UJIIndoorloc in terms of neuron numbers (a) Building 0, (b) Building 1, and (c) Building 2

Table 7. Confusion matrix (ELM-WAE) on UJIIndoorLoc test dataset

	Building 0				Building 1				Building 2				
Predicted Class	F1	F2	F3	F4	F1	F2	F3	F4	F1	F2	F3	F4	F5
F1	75	1	0	0	0	0	0	0	0	0	0	0	0
F2	3	207	3	0	0	0	0	0	0	0	0	0	0
F3	0	0	162	2	0	0	0	0	0	0	0	0	0
F4	0	0	0	83	0	0	0	0	0	0	0	0	0
F1	0	0	0	0	24	0	0	0	0	0	0	0	0
F2	0	0	0	0	5	142	2	0	0	0	0	0	0
F3	0	0	0	0	0	1	85	1	0	0	0	0	0
F4	0	0	0	0	0	0	0	46	0	0	0	0	0
F1	0	0	0	0	0	0	0	0	22	0	0	0	0
F2	0	0	0	0	0	0	0	0	2	109	0	0	0
F3	0	0	0	0	0	0	0	0	0	2	52	0	0
F4	0	0	0	0	0	0	0	0	0	0	1	39	4
F5	0	0	0	0	0	0	0	0	0	0	1	1	35
	Actual Class												

Although three different datasets have different feature spaces and targets, the optimal hyperparameters in different testbeds do not differ significantly, as shown in Table 5. To evaluate how each local optimal model performs on other datasets, we train the optimal model of each dataset on two other datasets. As shown in Table 8, accuracy although is not optimally global, but is not far from optimal results.

Table 8. Accuracy of a designed optimal model for each dataset when is applied to others for three datasets

Dataset	Accuracy (%) Optimal hyperparameters: N_{ae} / N_C / c_{cls} 60/300/10^{-6}	90/200/10^{-5}	90/300/10^{-6}	Number of Classes	Number of Aps
UJIIndoorLoc	97.30 *	95.94	96.12	13	520
TU	94.66	95.32*	95.12	5	992
UTS	95.36	95.88	96.39*	16	589

The star sign indicates the optimal model belongs to the relevant database.

The benchmark approaches and the comparison results are illustrated in Table 9 in terms of building and floor success rates. Our proposed approach and most of the compared methods achieve almost 100% accuracy in building prediction, showing that our proposed system can satisfyingly handle building classification. Meanwhile, the proposed method outperforms compared approaches with the highest floor success rate of 97.21%, 95.32% and, 96.39% on UJIIndoorLoc, Tampere, and, UTSIndoorLoc datasets, respectively. The values listed in this table are based on the results reported in the related papers, except for the following three methods which are based on our experimental results: ADELM [14], H-ELM [31], KNN, and ELM. In H-ELM, we set two layers of ELM-sparse-autoencoder with both 60 neurons, and 300 neurons set for the classification step. A dash, "- ", in Table 9 means the results are not mentioned in the relevant article.

Table 9. Comparison of proposed method accuracy and state and the art methods on the same testbed

Method		Dataset UJIIndoorLoc		Tampere	UTSIndoorLoc
Ref.	Name	Building hit rate	Floor hit rate	Floor hit rate	Floor hit rate
[30]	AFARLS	100	95.41	94.76	-
[28]	ScalableDNN	99.82	91.27	-	-
[34]	DeepL.	92	92	-	-
[35]	Mosaic	98.65	93.86	-	-
[20]	Storyteller	-	-	92	-
[36]	SIMO-DNN	-	-	94.13	-
[16]	CNNLoc	100	96.03	94.22	94.57
[37]	RTLS	100	94	-	-
[38]	HF-RF	99	96	-	-
[8]	RDL	-	94.60	-	-
[14]	ADELM	100	93.61	94.61	95.10
[31]	H-ELM	100	94.14	94.50	95.61
-	KNN (k=1)	100	91.26	90.26	-
-	ELM ($\beta = 1$)	99.91	91.53	88.8	90.97
	ELM	100	94.59	91.11	92.52
Proposed	ELM-WAE ($\beta = 1$)	100	93.97	94.51	94.33
	ELM-WAE*	100	97.30	95.32	96.39

6. CONCLUSION

This paper presents an effective method for floor/building identification in complex environments. This paper presents an effective method for floor/building identification in complex environments. The proposed building and floor detection methods in this study, consisting of three main steps; data preprocessing, feature extraction, and classification. In the first step, a new RSS scaling is proposed to deal with device heterogeneity and signal attenuation. In the second step, input dimension reduction and importance features extraction are implemented by ELM-WAE, and in the final step, floor level determination is carried out using ELM. The performance of the proposed building/floor identification is compared with state-of-the-art positioning methods based on three different available datasets. The experimental results demonstrate that our approach outperforms the existing techniques when is evaluated individually on UJIIndoorLoc, UTSIndoorLoc, and Tampere datasets by achieving an accuracy of 97.30%, 96.39%, and 95.32% respectively. In future work, we focus on using ensembles of our model to estimate the three-dimensional position, and how to achieve an optimal universal model exploiting transfer learning.

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