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Research Article

Device-Free Wireless Localization Using Artificial Neural Networks in Wireless Sensor Networks

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Currently, localization has been one of the research hot spots in Wireless Sensors Networks (WSNs). However, most localization methods focus on the device-based localization, which locates targets with terminal devices. This is not suitable for the application scenarios like the elder monitoring, life detection, and so on. In this paper, we propose a device-free wireless localization system using Artificial Neural Networks (ANNs). The system consists of two phases. In the off-line training phase, Received Signal Strength (RSS) difference matrices between the RSS matrices collected when the monitoring area is vacant and with a professional in the area are calculated. Some RSS difference values in the RSS difference matrices are selected. The RSS difference values and corresponding matrix indices are taken as the inputs of an ANN model and the known location coordinates are its outputs. Then a nonlinear function between the inputs and outputs can be approximated through training the ANN model. In the on-line localization phase, when a target is in the monitoring area, the RSS difference values and their matrix indices can be obtained and input into the trained ANN model, and then the localization coordinates can be computed. We verify the proposed device-free localization system with a WSN platform. The experimental results show that our proposed device-free wireless localization system is able to achieve a comparable localization performance without any terminal device.

1. Introduction

As Internet of Things (IoT) is becoming progressively popular, the related research areas that IoT involves have been well investigated, such as Wireless Sensors Networks (WSNs), Radio Frequency Identification (RFID), Micro-Electro-Mechanical System (MEMS), and mobile computing [1]. Among these, WSNs integrate various advanced technologies including sensor technology, wireless communication, and distributed information processing, so it has attracted great concerns in IoT [2, 3]. In a WSN, usually a number of sensor nodes are deployed in a monitoring area. These sensor nodes are connected through wireless communication to finish the tasks of sensing, recognizing, and monitoring in a cooperative manner. With the abilities of sensing, computing, and communicating, WSNs have been widely used in various fields, for example, indoor fire detection, object tracking, survivor sensing, and building safety monitoring [4]. In these applications, localization in WSNs plays an essential and important role [5].

So far, various localization systems have been developed [6–9]. Satellite-based localization system is able to provide satisfactory Location Based Service (LBS) for users in outdoor environments [10]. Cellular-based system is able to calculate the locations of mobile phone users, but the cellular-based system usually suffers great localization errors [11]. Most localization systems using Wireless Local Area Networks (WLANs) are able to offer LBS for users when the users take WLAN terminal devices [12, 13]. Ultrawide Band (UWB) localization system needs users to take UWB tags for estimating their locations [6]. Smart phone sensors are also used for navigation and localization services [14]. Although infrared-based localization system does not need terminal devices, the performance can be easily affected by

surrounding environments [6]. In a word, most existing localization systems need users to carry terminal devices, which cannot be applied in some special scenarios like the elder monitoring, life detection, and so on. Device-free wireless localization in WSNs that makes use of Received Signal Strength (RSS) variations between sensor nodes is able to solve this problem. When a target goes into the monitoring area of a WSN, the presence of the target will reflect, scatter, and absorb the radio signals of the WSN [15]. Localization results can be calculated with the collected RSS variations. Therefore, device-free wireless localization that does not need any terminal device extends the application range of localization and it will have a promising prospect and increasing requirement.

However, one challenge of the device-free wireless localization in WSNs is the unpredictability of the RSS measurements in multipath environments, especially in the complex environments where people usually move. To deal with this problem, in this paper, we refer to the popular WLAN fingerprinting localization method [6] and propose a device-free wireless localization system using Artificial Neural Networks (ANNs). In our proposed system, RSS difference values and corresponding matrix indices are fused as the inputs of an ANN model, whose outputs are location coordinates. Then a nonlinear function between the inputs and outputs can be approximated through training the ANN model. When we need to locate a target in the monitoring area, the trained ANN model is used to compute the localization coordinates of the target. The four contributions of this paper can be summarized as follows:

(1) We propose a device-free wireless localization system using an ANN model. The localization system consists of two phases: the off-line training and on-line localization. In the off-line phase, a professional stands at some selected locations with known location coordinates. RSS difference matrices between the RSS matrices collected when the monitoring area is vacant and with the professional in the area are computed. Some RSS difference values and corresponding matrix indices are used as the inputs, and the known location coordinates are used as the outputs for training the ANN model. In the on-line phase, when a target is in the monitoring area, the obtained RSS difference values and matrix indices are input into the trained ANN model for location coordinate estimation.

(2) We propose an ANN model for location coordinate estimation in our device-free wireless localization system. The proposed ANN model is not only used for nonlinear function approximation, but also used for data fusion. The model fuses the RSS difference values and corresponding matrix indices and then takes the fused data as the input vector of the ANN model. With the known location coordinates as the output vector, a nonlinear function can be approximated with the ANN model for computing the localization results.

(3) We build a hardware platform for the device-free wireless localization system with a ZigBee-based WSN. It consists of 16 sensor nodes, 1 sink node, and 1 localization server. Each sensor node sends the RSS data that are received from the other sensor nodes to the localization server through the sink node. The RSS data will be processed and then used to calculate localization results in the server.

(4) We verify the proposed localization system in a real indoor environment with our built hardware platform. We also try different system parameters for localization performance improvement and analyse the experimental results. The experimental results confirm that our proposed device-free wireless localization system is able to achieve a comparable localization performance.

The remainder of the paper is organized as follows. Related works about this research are reviewed in Section 2. In Section 3, the proposed device-free wireless localization system and ANN model for estimating localization results are given in detail. Section 4 describes the experimental hardware platform, experimental results, and analyses. Finally, conclusions are drawn and ideas for future works are presented in Section 5.

2. Related Works

So far, many device-free wireless localization methods have been proposed. Wilson and Patwari [16] presented a device-free localization method based on Radio Tomographic Imaging (RTI). RTI-based localization method imaged the RSS attenuation caused by targets with inexpensive and standard hardware [17]. They also proposed regularization methods to reduce noise and a statistical model relating variance to spatial locations of movement for motion image estimation [18]. Due to the comparable performance of this method, RTI-based device-free localization has been extensively researched. An RTI-based device-free localization using segmentation algorithm and connected component label algorithm for target tracking was proposed in [19]. Nannuru et al. [20] developed a model for multitarget tracking using RTI in indoor environments and successfully tracked three targets with the model. Bocca et al. [21] presented an RTI method that used RSS measurements on multiple frequency channels and combined them with a weighted average for real-time multitarget tracking. Alippi et al. [22] proposed an RTI method for locating people outdoors that achieved high localization accuracy and reduced the sensor energy consumption. Wang et al. [23–25] also have done solid works in this area and they applied saddle surface model, compressive sensing (CS), and Bayesian grid approach into device-free wireless localization. Savazzi et al. [26] proposed the uses of device-free localization methods and architectures to track a human worker in a human-robot industrial scenario. The proposed localization and detection algorithm was based on the jump linear Markovian and interactive multiple model. Wang et al. [15] introduced an energy-efficient framework for multitarget device-free localization. They applied CS to guarantee high localization performance with less RSS measurements.

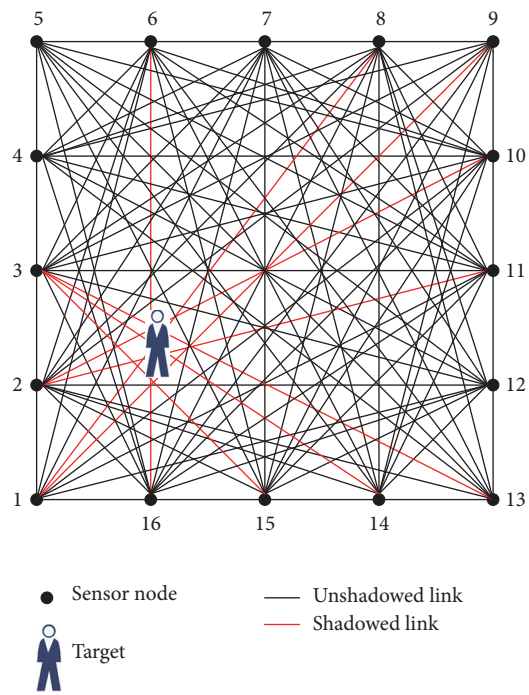

Figure 1: The device-free wireless localization system that consists of 16 sensor nodes.

Besides the aforementioned, similar to WLAN fingerprinting localization method, Zhang et al. [27] mounted some nodes on the ceiling and divided the tracking area into different subareas. For each subarea, they utilized the Support Vector Regression (SVR) model to estimate the localization coordinates. Youssef et al. [28] proposed a device-free wireless localization system based on radio-map. They calculated localization results with a probabilistic method. Then they proposed another device-free localization system with particle filtering [29]. Xu et al. [30] formulated the device-free localization problem with probabilistic classification approaches based on discriminant analysis and mitigated the errors caused by multipath effect. Because the fingerprinting localization method performs well in multipath environments, in this paper, we also refer to the fingerprinting localization method and propose a device-free localization system using an ANN model.

3. Proposed Device-Free Localization System

3.1. System Overview. The proposed device-free localization system is shown in Figure 1. The sensor nodes are evenly deployed on the edges of a square monitoring area. When a target goes into the monitoring area, some wireless links between sensor nodes will be shadowed. If we take Figure 1 as an example, the wireless links between sensor nodes 1 and 8, 1 and 9, 2 and 10, 2 and 11, 3 and 13, 3 and 14, 3 and 15, and 6 and 16 are shadowed, which cause RSS variations of these wireless links. When the target moves to a different location in the monitoring area, corresponding wireless links will be also shadowed. All the sensor nodes in the WSN measure the RSS data and send the data to a localization server through a sink node. We assume L sensor nodes have been deployed in the monitoring area with known location coordinates (x_i, y_i), $i = 1, 2, \cdots, L$, then we can have $M = L(L-1)/2$ wireless links. The RSS data of these wireless links are sent to the sink node and then processed in the localization server. When the monitoring area is vacant, that is, no target is in the area, we collect the RSS data from the WSN and compile them into matrices. Then a professional stands at a number of selected locations with known location coordinates, and some wireless links are shadowed when the professional is at each location. We can also obtain the RSS matrices in the same manner and compute the RSS difference matrices. We establish a nonlinear function relationship between the RSS difference value information and location coordinates with an ANN model. This ANN model is used for calculating the location coordinates of the target in the monitoring area.

Based on the description above, more specifically, the proposed device-free wireless localization system consists of two phases: the off-line training and on-line localization. In the off-line training phase, we first collect the RSS data of the vacant monitoring area for a while. The RSS data of all the sensor nodes in the WSN are sent to the localization server through the sink node. The server will extract the RSS data and compile the data into RSS matrices. Then a number of specific locations are selected and their location coordinates are recorded. A professional stands at each location and the RSS data from all the sensor nodes are also collected and processed in the same manner in order to get the RSS matrices. The RSS difference matrices between the RSS matrices collected when the monitoring area is vacant and with the professional in the area are computed. Some RSS difference values are selected, and then these RSS difference values and their matrix indices are fused and input into the ANN model. Meanwhile, the known location coordinates of the selected locations are considered as the outputs of the ANN model. So the ANN model can be trained with these data and a nonlinear function is approximated for calculating localization coordinates. In the on-line localization phase, when a target goes into the monitoring area, some wireless links are shadowed. The localization server collects the RSS data from all the sensor nodes and compiles these RSS data into an RSS matrix. Then an RSS difference matrix is also computed. The same number of selected RSS difference values and their indices in the matrix are input into the trained ANN model, and therefore the location coordinates of the target can be calculated by the ANN model.

3.2. RSS Data Preprocessing. After the localization server collects enough broadcasted frames in the WSN that consist of RSS and Node Identification (NID) data, the RSS data can be extracted from these frames and compiled into an RSS matrix with dimensions of $L \times L$. The row of the RSS matrix represents the sensor node that receives the radio signals and the column of the RSS matrix represents the sensor node that transmits the radio signals. So the RSS matrix of the vacant monitoring area can be denoted by the following:

$$\mathbf{RSS} = \begin{bmatrix} 1 & RSS_{1,2} & \cdots & RSS_{1,L} \\ RSS_{2,1} & 2 & \cdots & RSS_{2,L} \\ \vdots & \vdots & \ddots & \vdots \\ RSS_{L,1} & RSS_{L,2} & \cdots & L \end{bmatrix}_{L\times L} \tag{1}$$

When a professional stands at ith location, the compiled RSS matrix can be denoted by the following:

$$\mathbf{rss}_i = \begin{bmatrix} 1 & rss_{1,2,i} & \cdots & rss_{1,L,i} \\ rss_{2,1,i} & 2 & \cdots & rss_{2,L,i} \\ \vdots & \vdots & \ddots & \vdots \\ rss_{L,1,i} & rss_{L,2,i} & \cdots & L \end{bmatrix}_{L\times L}, \quad i = 1, 2, \cdots, Q \tag{2}$$

where Q is the number of selected locations. So the RSS difference matrix $\Delta\mathbf{rss}_i$ between $\mathbf{RSS}$ and $\mathbf{rss}_i$ can be computed by the following:

$$\Delta\mathbf{rss}_i = \left|\mathbf{rss}_i - \mathbf{RSS}\right|, \quad i = 1, 2, \cdots, Q \tag{3}$$

As shown in Figure 1, there is one problem that should be considered that is the sensor nodes on the same edge of the monitoring area can also receive RSS data from each other. For instance, sensor node 1 can receive the RSS data from sensor node 5 and sensor node 13. Sometimes the RSS difference values between these sensor nodes on the same edge may vary greatly. Because this is not caused by the target in the monitoring area, if we take these RSS difference values into consideration and input the RSS difference values and their matrix indices into the ANN model, the localization errors might be significant. So we design a filtering matrix $\mathbf{m}$ to set the elements that represent the RSS difference values between the sensor nodes on the same edges of the monitoring area to be 0. This operation is able to remove the negative effect effectively. The final RSS difference matrix $\Delta\mathbf{rss}_i'$ after the filtering operation can be computed by the following:

$$\Delta\mathbf{rss}_i' = \Delta\mathbf{rss}_i \bullet \mathbf{m}, \quad i = 1, 2, \cdots, Q \tag{4}$$

3.3. Localization with ANN Model. In this paper, we apply a three-layer perceptron network for nonlinear function approximation and data fusion. The network has a basic network structure that consists of one input layer, one hidden layer, and one output layer. The structure of the network is shown in Figure 2. Let the number of the neurons in the input layer, hidden layer, and output layer be $3K$, T, and 2, respectively. After the RSS data preprocessing, we can obtain the RSS difference matrix $\Delta\mathbf{rss}_i'$. We sort all the elements in matrix $\Delta\mathbf{rss}_i'$ in a descending order, then we select the first K maximum RSS difference values $\Delta rss_{i,j}'$, $j = 1, 2, \cdots, K$, and determine their indices in matrix $\Delta\mathbf{rss}_i'$ that are column $c_{i,j}$ and row $r_{i,j}$, $j = 1, 2, \cdots, K$. The RSS difference values and their indices are fused by the three-layer ANN model as the input vector of the ANN model denoted as $(\Delta rss_{i,1}', c_{i,1}, r_{i,1}, \Delta rss_{i,2}', c_{i,2}, r_{i,2}, \cdots, \Delta rss_{i,K}', c_{i,K}, r_{i,K})$. Meanwhile, the outputs of the ANN model are the location coordinates (x_i, y_i) in X-axis and Y-axis, respectively. Then the nonlinear function between the inputs and outputs can be approximated and denoted by $F : \mathbb{R}^{3K} \to \mathbb{R}^2$ as follows:

$$(x_i, y_i) = F\left(\Delta rss_{i,1}', c_{i,1}, r_{i,1}, \Delta rss_{i,2}', c_{i,2}, r_{i,2}, \cdots, \Delta rss_{i,K}', c_{i,K}, r_{i,K}\right), \quad i = 1, 2, \cdots, Q \tag{5}$$

When we input the vector $(\Delta rss_{i,1}', c_{i,1}, r_{i,1}, \Delta rss_{i,2}', c_{i,2}, r_{i,2}, \cdots, \Delta rss_{i,K}', c_{i,K}, r_{i,K})$ into the ANN model, the output $g_N^{(j)}$ of jth neuron in the Nth layer of the model can be calculated by the following:

$$\begin{aligned} g_N^{(j)} &= f\left(u_N^{(j)}\right) \\ u_N^{(j)} &= \sum_{i=1}^{I} \omega_{N-1,N}^{(i,j)} x_{N-1,N}^{(i,j)} - \theta_N^{(j)} \\ j &= 1, 2, \cdots, T, \ I = 3K, \ N = 2; \ j = 1, 2, \ I = T, \ N = 3 \end{aligned} \tag{6}$$

where $x_{N-1,N}^{(i,j)}$ is the input from ith neuron in the $(N-1)$th layer to jth neuron in the Nth layer; $\omega_{N-1,N}^{(i,j)}$ is the weight from ith neuron in the $(N-1)$th layer to jth neuron in the Nth layer; $\theta_N^{(j)}$ is the threshold of jth neuron in the Nth layer; $f(\cdot)$ is the activation function of the ANN model.

We train the ANN model with the famous back propagation (BP) algorithm [31], which has been widely used for ANN training. The operation process of the algorithm is to propagate errors backwards and update the weights and thresholds of the network. The updating process will be suspended when one of the iteration termination conditions is achieved. The weights and thresholds of the ANN model can be updated by the following:

$$\begin{aligned} \omega_{N-1,N}^{(i,j)} &= \omega_{N-1,N}^{(i,j)} + a\delta_N^{(j)} g_{N-1}^{(j)} \\ \theta_N^{(j)} &= \theta_N^{(j)} - b\delta_N^{(j)} \\ \delta_N^{(j)} &= \begin{cases} \sum_{m=1}^{2} \delta_{N+1}^{(m)} \omega_{N,N+1}^{(i,m)} f'\left(u_N^{(j)}\right), & N = 2 \\ \left[o^{(j)} - g_N^{(j)}\right] f'\left(u_N^{(j)}\right), & N = 3 \end{cases} \\ & i = 1, 2, \cdots, 3K, \ j = 1, 2, \cdots, T, \ N = 2; \ i = 1, 2, \cdots, T, \ j = 1, 2, \ N = 3 \end{aligned} \tag{7}$$

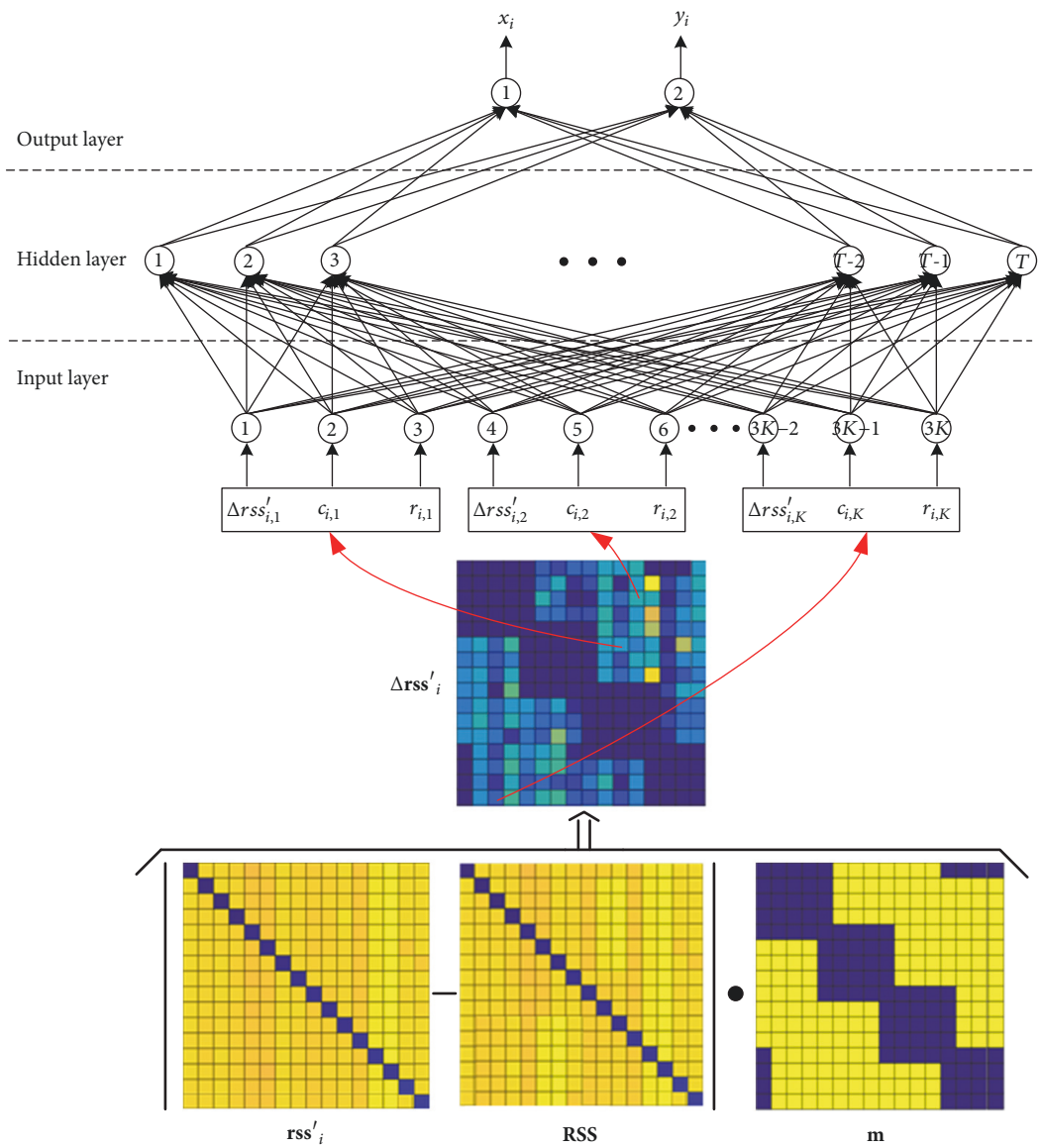

Figure 2: Proposed ANN structure and its inputs and outputs.

where $o^{(j)}$ is our expected output of jth neuron in the output layer; a and b are learning rates for adapting the stability and training time.

After finishing the ANN model training, when a target is in the monitoring area in the on-line localization phase, the shadowed RSS data of the WSN are collected and processed. Then the first K maximum RSS difference values and their matrix indices are fused as the input vector $(\Delta rss'_1, c_1, r_1, \Delta rss'_2, c_2, r_2, \cdots, \Delta rss'_K, c_K, r_K)$ and input into the trained ANN model. So the location coordinates $(\hat{x}, \hat{y})$ of the target can be estimated with the trained ANN model by the following:

$$(\hat{x}, \hat{y}) = F\left(\Delta rss'_1, c_1, r_1, \Delta rss'_2, c_2, r_2, \cdots, \Delta rss'_K, c_K, r_K\right) \quad (8)$$

4. Experimental Setup, Results, and Analyses

4.1. Experimental Setup. In this paper, we use CC2530 ZigBee nodes of Texas Instruments (TI) as the WSN nodes. This CC2530 ZigBee node has the advantages of low power cost, high controllability, and convenient networking. It operates on the 2.4GHz ISM band and is also compatible with IEEE 802.15.4 protocol. When one sensor transmits radio signals, all the other sensor nodes in the network can receive the signals. In our experiment, the hardware platform consists of 16 sensor nodes, 1 sink node, and 1 localization server. The 16 sensor nodes measure the RSS data and transmit these RSS data in turn. The sink node is used to receive the RSS data from all the sensor nodes and also upload these data to the localization server.

In this experiment, we set that each sensor node is able to transmit radio signals and the other sensor nodes can

Transmitting node NID	NID 1	RSS 1	……	NID 16	RSS 16

Figure 3: Structure of the transmitted frame

Figure 4: Photography of the experimental scenario.

receive these radio signals and measure the RSS data. To be more specific, a total of 16 sensor nodes are first evenly deployed on the edges of the square monitoring area. After the network start-up, one sensor node can broadcast its NID. The other 15 sensor nodes are able to receive the NID and measure the RSS data. The RSS and corresponding NID data are recorded in a frame and then the frame is also transmitted. The designed structure of the frame is shown in Figure 3. We set different time delays for different sensor nodes in order to avoid conflicts. When it is the turn of one sensor node to transmit its frame, the node will transmit its NID as well as the measured RSS data and corresponding NID information. After a while, every frame will contain the entire RSS data and NID information of all the nodes. The sink node can also receive all the frames in the WSN and upload these data to the localization server.

The real experimental scenario is shown in Figure 4. The monitoring area that is in a meeting room is a square area with dimensions of 7.2m×7.2m. There are three tables and some chairs in the monitoring area. The monitoring area plan is shown in Figure 5 and the chairs are not displayed in the plan for simplicity. The deployed 16 sensor nodes are on the edges of the monitoring area with 1.8m gaps and are also fixed on tripods with 1.2m height. The sink node and localization server are in the meeting room too, but they are not in the monitoring area. In the monitoring area, there are 52 locations are selected, which are marked with "×" in Figure 5. The RSS data that are collected for each location can be compiled into 20 RSS matrices. We divide these RSS matrices into two data sets. One set is used for training the ANN model and the other set is used as testing data.

4.2. Experimental Results and Analyses. In this experiment, we set the number of neurons in the hidden layer to be 35 and we train the ANN model with BP algorithm. We utilize 15 RSS matrices of each selected location to train the ANN model and the rest of 5 RSS matrices to test the trained model. We calculate the mean errors of the localization results with the number of first K maximum RSS difference values varying from 1 to 10. Figure 6 shows the mean errors with different parameter K. The maximum mean error is 1.31m when K equals 9 and the minimum one is 0.42m when K equals 6. The reason might be that when K is set to be too large, the

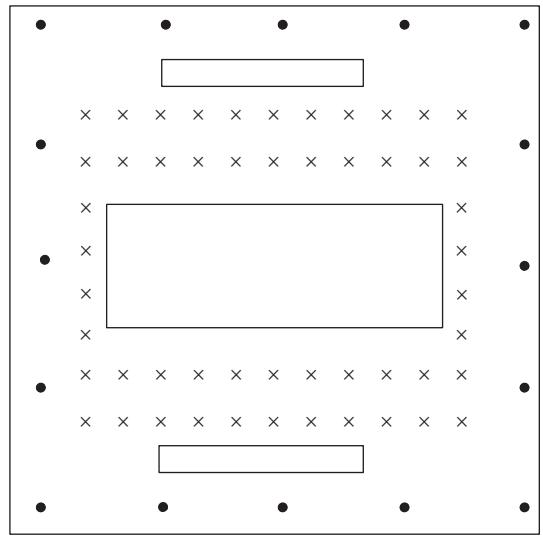

Figure 5: Monitoring area plan.

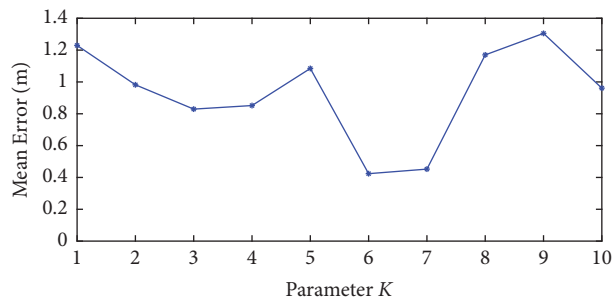

Figure 6: Mean errors with different parameter K.

number of inputs is $3K$, the performance of the ANN model decreases because there are only 35 neurons in the hidden layer. On the contrary, when K is set to be too small, the selected RSS difference values may be not caused by the target, so it is difficult to estimate the location coordinates of the target accurately. For example, when parameter K equals 2, only the first 2 maximum RSS difference values are selected. At this time, if it is not the target but some interference causes the RSS variations, then this will decrease the localization performance.

As presented in Table 1, the localization results with parameter K varying from 3 to 8 are compared. The error standard deviations with parameter K varying from 3 to 8 are 1.05, 1.15, 1.14, 1.08, 1.45, and 1.35, respectively. When parameter K increases to 7 or 8, the error standard deviation increases greatly. Meanwhile, the cumulative probabilities with parameter K varying from 3 to 8 within localization error of 1m are 75.4%, 76.4%, 60.4%, 83.5%, 79.2%, and 63.1%, respectively. The cumulative probabilities with parameter K varying from 3 to 8 within localization error of 2m are 91.5%, 88.1%, 83.5%, 90.0%, 87.7%, and 77.7%, respectively. The cumulative probabilities with different parameter K are also shown in Figure 7. Obviously, the localization performance of the proposed system when K equals 6 outperforms the others.

Table 1: Performance comparison with different parameter K.

K	Mean error (m)	Standard deviation (m)	Accuracy within 1m (%)	Accuracy within 2m (%)
3	0.83	1.05	75.4	91.5
4	0.85	1.15	76.4	88.1
5	1.08	1.14	60.4	83.5
6	0.42	1.08	83.5	90.0
7	0.45	1.45	79.2	87.7
8	1.17	1.35	63.1	77.7

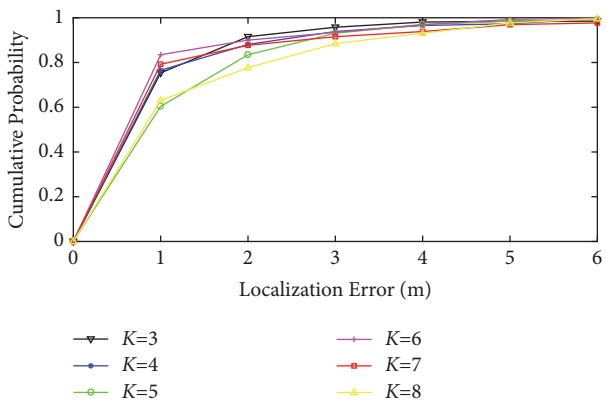

Figure 7: Cumulative probabilities with different parameter K.

5. Conclusions and Future Works

In this paper, a device-free wireless localization system using an ANN model is proposed. With the proposed localization system, location coordinates of a target can be estimated without any terminal device attached. We construct a WSN hardware platform with ZigBee nodes and RSS data of wireless links between the sensor nodes are collected. We compile the RSS data into RSS matrices and then compute the RSS difference matrices between the RSS matrices collected when the monitoring area is vacant and with a professional in the monitoring area. The first K maximum RSS difference values that are caused by the professional are selected. These RSS difference values and their matrix indices are taken as the inputs and the known location coordinates are used as the outputs to train the ANN model. In the on-line localization phase, when a target is in the monitoring area, the same number of RSS difference values and corresponding matrix indices can be obtained and input into the trained ANN model, then the localization coordinates can be calculated. The experimental results prove that our proposed device-free wireless localization system is able to achieve a comparable localization performance without any terminal device.

In the future, we will try to focus on the moving target or multitarget localization with the constructed hardware platform and the system parameter optimization for localization performance improvement. The nonlinear function approximation with other advanced machine learning algorithms will be investigated as well.

Data Availability

The data supporting the findings of this study are available within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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