ZigBee-Based Device-Free Wireless Localization in Internet of Things

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Abstract. In recent years, localization has been one of the research hot-spots in Internet of Things (IoT). Device-Free Wireless Localization (DFWL) that extends the application range of wireless localization has been considered as a promising technology. In this paper, we propose a ZigBee-based DFWL system using Artificial Neural Networks (ANNs) in IoT. The proposed system utilizes Received Signal Strength (RSS) variations, which is caused by the obstructing of the Line of Sight (LoS) links, to estimate the location of a target using an ANN model. A non-linear function is approximated between RSS difference information and location coordinates using the ANN model. With the ANN model, the location of the target can be estimated. The experimental results show that the proposed DFWL system is able to locate the target without any terminal device and offer a valuable reference for DFWL in IoT.

Keywords: Device-free wireless localization · Internet of Things
Artificial neural networks · ZigBee

1 Introduction

With the rapid development of information technology and Internet of Things (IoT), Location-Based Service (LBS) has drew more and more attentions [1,2], especially in some special application scenarios like museum, shopping mall, and airport, where users have an increasing demand for LBS. However, most of the existing developed localization systems need users to carry terminal devices like Wireless Local Area Networks (WLANs), Ultra Wideband (UWB), and Radio Frequency Identification (RFID) [3–5], which is not suitable for some special application scenarios such as life detection, the elder monitoring and so on. To solve this problem, Device-Free Wireless Localization (DFWL) system that utilizes Received Signal Strength (RSS) variations to estimate the location of a target has played an important role [6]. Therefore, in this paper, we propose a ZigBee-based DFWL system in IoT that is able to sense and locate a target in an Area of Interest (AoI) without any terminal device.

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2 Related Works

Until now, many DFWL systems have been developed. One of the famous systems presented by Wilson and Patwariis was the DFWL based on Radio Tomographic Imaging (RTI) [6,7]. Due to the comparable localization performance of RTI-based DFWL, some other RTI-based DFWL systems were proposed as well [8,9]. Wang et al. applied saddle surface model, compressive sensing (CS), and Bayesian grid approach into DFWL and obtained significant achievements [10–12]. An energy-efficient framework for DFWL was proposed in [13]. The researchers also applied CS to guarantee high localization accuracy with less RSS measurements.

Referring to the fingerprinting localization method [4], Zhang et al. mounted some nodes on the ceiling and divided the tracking area into different triangle areas. They used Support Vector Regression (SVR) to estimate target locations in each area [14]. Youssef et al. first proposed a DFWL system based on radio-map. They computed localization results with probabilistic method [15]. Then they proposed a different DFWL system using particle filtering [16]. Xu et al. formulated the DFWL problem with probabilistic classification methods based on discriminant analysis and mitigated the errors caused by multipath effect [17]. Because the fingerprinting localization method has been proved that it performs well in multipath environments, we refer to this method and propose a DFWL system using Artificial Neural Networks (ANNs) in this paper.

3 Proposed Device-Free Wireless Localization System

3.1 System Overview

As shown in Fig. 1, the sensor nodes of the proposed DFWL system are deployed evenly in the edges of an AoI. When a target goes into the AoI, some wireless links between sensor nodes are obstructed. RSS variations caused by the target in the AoI are sensed and used for estimating the location of the target. If we take Fig. 1 as an example, the wireless links between sensor nodes 1 and 8, 2 and 10, 2 and 11, 3 and 13, 3 and 14 as well as 6 and 16 are obstructed, so the RSS variations of these wireless links are caused by the target. If we assume L sensor nodes have been deployed in the AoI with known location coordinates, then there will be $H = \frac{L\times(L-1)}{2}$ wireless links. All the sensor nodes in the system send the measured RSS data to a sink node and then the sink node forwards these data to a localization server where the location coordinates of the target are computed. When the monitoring area is vacant, we collect the RSS data and compile them into RSS matrices. When a professional stands at a number of selected locations with known location coordinates in the AoI, some relative wireless links are obstructed and then RSS data are collected. We can also compile these RSS data into the RSS matrices and compute the RSS difference matrices. We take some RSS difference values and their matrix indices as the inputs of an ANN model, and also take the known location coordinates

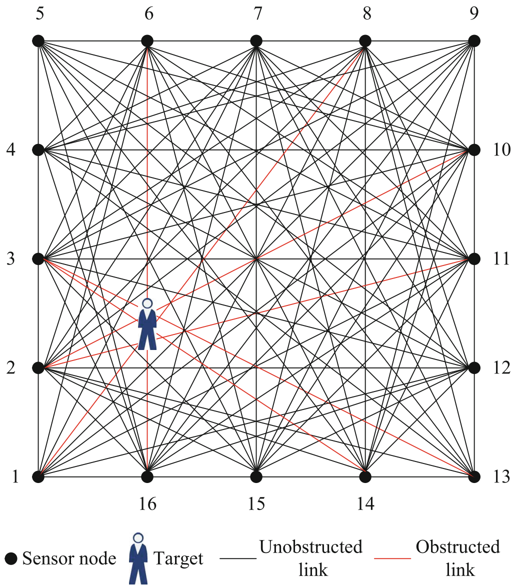

Fig. 1. The proposed DFWL system with ZigBee sensor nodes.

as the outputs of the model. A nonlinear function between the RSS difference information and location coordinates can be approximated with the ANN model, which is used for estimating the location coordinates of the target.

3.2 RSS Difference Matrix Calculation

When the localization server receives enough RSS data from a vacant AoI, these RSS data are compiled into an RSS matrix $\mathbf{R}$ with dimensions of $L \times L$ that can be denoted by (1). The row of the RSS matrix $\mathbf{R}$ represents the sensor node that receives the RSS data and the column of the RSS matrix $\mathbf{R}$ represents the sensor node that sends these data.

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

When a professional stands at ith location that is selected in the AoI, the RSS data can be collected and compiled into an RSS matrix $\mathbf{r}_i$ with the same dimensions denoted by:

$$\mathbf{r}_i = \begin{bmatrix} 1 & r_{1,2,i} & \cdots & r_{1,L,i} \\ r_{2,1,i} & 2 & \cdots & r_{2,L,i} \\ \vdots & \vdots & \ddots & \vdots \\ r_{L,1,i} & r_{L,2,i} & \cdots & L \end{bmatrix}_{L \times L} \quad , i = 1, 2, \cdots, M \tag{2}$$

where, M is the number of selected locations. So the RSS difference matrix $\Delta\mathbf{s}_i$ between $\mathbf{R}$ and $\mathbf{r}_i$ can be computed by:

$$\Delta\mathbf{s}_i = \left|\mathbf{R} - \mathbf{r}_i\right|, i = 1, 2, \cdots, M \tag{3}$$

Sometimes, the RSS data between the sensor nodes in the same edge may vary greatly due to some interference. If these data are used for localization, the localization errors might be significant. In order to eliminate the negative effect, we design a matrix $\mathbf{m}$ to set all the RSS difference values between the sensor nodes in the same edge of the AoI to be 0. So we calculate the final RSS difference matrix $\Delta\mathbf{s}'_i$ as follows:

$$\Delta\mathbf{s}'_i = \Delta\mathbf{s}_i\mathbf{m}, i = 1, 2, \cdots, M \tag{4}$$

When a target moves into the AoI, the real-time RSS data are sent to the localization server and then the RSS difference matrix can be computed in the same manner as mentioned above.

3.3 Proposed ANN Model for Localization

Because ANNs have a superior performance in nonlinear function approximation and data fusion, a three-layer perceptron network is applied as the proposed ANN model in this paper. As shown in Fig. 2, The proposed ANN model consists of one input layer, one hidden layer, and one output layer, and the numbers of the neurons in the three layers are $3K$, N, and 2, respectively. After obtaining the RSS difference matrix $\Delta\mathbf{s}'_i$, all the RSS difference values are sorted in a non-increasing order. Then the first K maximum RSS difference values $\Delta s'_{i,j}, j = 1, 2, \cdots, K$ are selected and the indices of these values in matrix $\Delta\mathbf{s}'_i$ that are column $c_{i,j}$ and row $r_{i,j}, j = 1, 2, \cdots, K$, are determined. Then we fuse the RSS difference values and their indices as the input vector of the ANN model denoted by $\left(\Delta s'_{i,1}, c_{i,1}, r_{i,1}, \cdots, \Delta s'_{i,K}, c_{i,K}, r_{i,K}\right)$. At the same time, we take the location coordinates where the professional stands as the output vector denoted by (x_i, y_i). Then the nonlinear function between the input vector and output vector can be approximated through training the ANN model. The nonlinear function f can be denoted by:

$$(x_i, y_i) = f\left(\Delta s'_{i,1}, c_{i,1}, r_{i,1}, \cdots, \Delta s'_{i,K}, c_{i,K}, r_{i,K}\right), i = 1, 2, \cdots, M \tag{5}$$

After the training of the ANN model, when a target moves in and stands at a location in the AoI, the collected RSS data are processed in the same way and the RSS difference matrix $\Delta\hat{\mathbf{s}}'$ can be computed. The first K maximum RSS difference values $\Delta\hat{s}'_j, j = 1, 2, \cdots, K$, as well as the indices of these values $\hat{c}_j$ and $\hat{r}_j, j = 1, 2, \cdots, K$, are fused as an input vector $(\Delta\hat{s}'_1, \hat{c}_1, \hat{r}_1, \cdots, \Delta\hat{s}'_K, \hat{c}_K, \hat{r}_K)$. Then the location coordinates $(\hat{x}, \hat{y})$ of the target are estimated with the non-linear function f by:

$$(\hat{x}, \hat{y}) = f\left(\Delta\hat{s}'_1, \hat{c}_1, \hat{r}_1, \cdots, \Delta\hat{s}'_K, \hat{c}_K, \hat{r}_K\right) \tag{6}$$

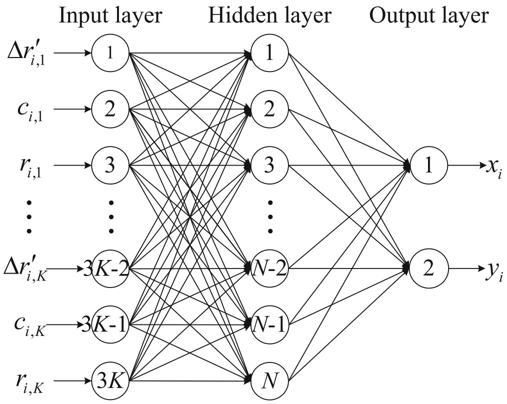

Fig. 2. The proposed three-layer ANN structure.

4 Experimental Setup, Results, and Analyses

4.1 Experimental Setup

In this paper, we adopt CC2530 ZigBee nodes as the experimental nodes. There are 16 sensor nodes and 1 sink node. The sensor nodes are deployed evenly in the edge of the experimental area with 1.8 m gaps and they are fixed on tripods with a height of 1.2 m. The plan of the experimental area is shown in Fig. 3. There are some chair and desks in the AoI and the sink node and localization server are not in the experimental area. A total of 52 locations are selected and their location coordinates are recorded. As shown in Fig. 3, the ZigBee sensor nodes are denoted by the black dots and the selected locations are denoted by the black crosses.

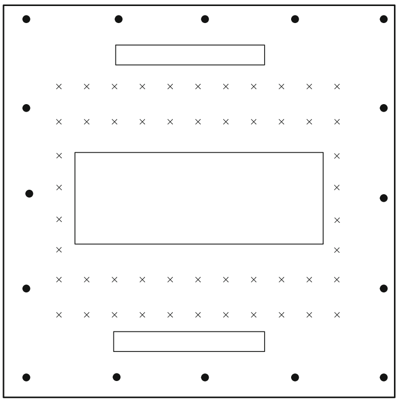

Fig. 3. Plan of the experimental area.

After the network startup, we collect enough RSS data and then compile them into 20 RSS matrices for each selected location. These data are divided into two data sets. One set that consists of 10 RSS matrices of each location is used for training the ANN model and the rest half of the data are used for testing the ANN model. The ANN model is trained with the famous back propagation algorithm. The experimental scenario is shown in Fig. 4.

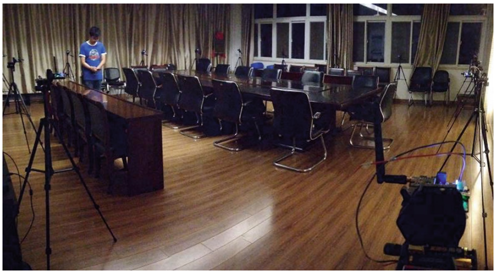

Fig. 4. Photography of the experimental scenario.

4.2 Experimental Results and Analyses

In the experiment, we set parameter K to be 5, which means the first 5 maximum RSS difference values are selected, and the number of neurons in the hidden layer to be 35. With the trained ANN model, localization results are computed. The mean error of the localization results is 0.98 m and the error standard deviation is

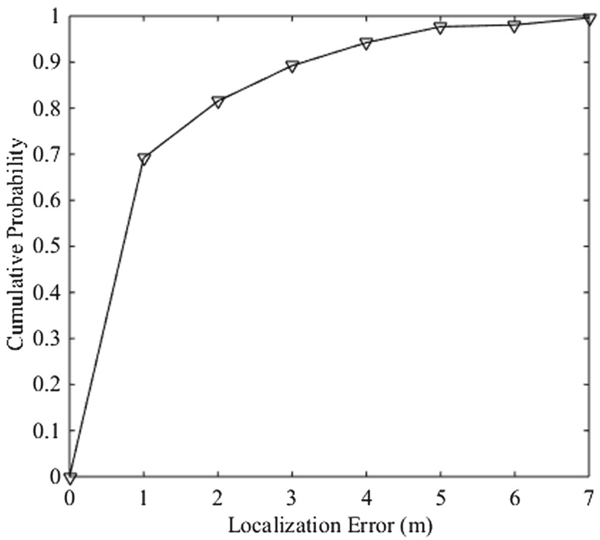

Fig. 5. Cumulative probability curve of the proposed DFWL system.

1.42 m. The cumulative probabilities within localization error of 1 m and 2 m are 69.2% and 81.5%, respectively. The cumulative probability curve of the proposed DFWL is shown in Fig. 5. Compared with the state of the art DFWL systems, the performance of the proposed DFWL system is not superior. The reasons may be the number of the training RSS data is not sufficient and the parameters of the proposed DFWL system are not optimal. So we may subsequently collect more RSS data for training the ANN model as well as optimize numbers of selected RSS difference values and neurons in the hidden layer to achieve a better localization performance.

5 Conclusions

In the paper, we propose a ZigBee-based DFWL system in IoT. This system utilizes RSS variations caused by a target in the AoI to locate the target without any terminal device. RSS data are collected and compiled into RSS matrices. Then the RSS difference values between the RSS matrices collected when the AoI is vacant and with a professional standing in it are computed. The first K maximum RSS difference values and their matrix indices are determined and also used as inputs. Meanwhile, the location coordinates of the professional are used as outputs to train the ANN model. When a target enters into the AoI, the RSS difference values are computed in the same way, then the selected RSS difference values and their indices in the RSS difference matrix are input into the trained ANN model, so the location coordinates of the target can be calculated. The experimental results demonstrate that the proposed DFWL system is able to locate the target in the AoI without any terminal device and offer a valuable reference for the DFWL in IoT.

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