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A ZigBee Indoor Positioning Scheme using Signal-Index-Pair Data Preprocess Method to Enhance Precision

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Abstract—**This paper develops a ZigBee indoor positioning scheme based on the location fingerprinting approach. The proposed scheme includes four workflows: (1) creating the location fingerprint table, (2) training the locating model using neural network (NN), (3) preprocessing data through the Signal-Index-Pair method, and (4) estimating the coordinate of the mobile target instantly. Testing results show that within the error distance of 5 meters, the NN locating model with the Signal-Index-Pair data preprocess method can increase the positioning precision by 17% compared with the original NN, in terms of the cumulative error probability (CEP). It also achieves 5% CEP higher than the k (k=5) nearest neighbor method and the weighted k (k=5) nearest neighbor method. Potential applications include patient tracking in hospitals, object tracking for factory monitoring, self-navigation of autonomous robots, and visitors monitoring in military buildings, and so on.**

I. INTRODUCTION

ZigBee is a wireless networking standard that is aimed at remote control and sensor applications with low data rates and needing low power consumption. It can operate in harsh radio environments and isolated locations. Consequently, ZigBee has been applied in many home and industrial applications, including lighting control, remote reading of electric meters, wireless smoke detecting, medical sensing and monitoring, building automation, etc. In particular, the RSS provided by ZigBee can be used for creating indoor positioning services for locating personnel and equipment. In addition, a ZigBee network can have up to 65535 devices, making ZigBee very suitable to be applied to create indoor positioning systems as valued-added applications [1][2].

The indoor environmental factors, such as floor levels and walls, cause channel fading, shadow fading, and multi-path fading during signal transmission. In addition, simultaneously using equipment that works around the same frequency equaling 2.4 GHz, such as WiFi devices, microwave, indoor wireless telephones, and Bluetooth equipment, will also generate interferences on the signal. Thus, it is hard to create a signal propagation model that can fit the actual situation [3][4]. In turn, signal-model-based indoor positioning techniques usually have low precision. Therefore, an alternative approach, called location fingerprinting, were broadly used in developing indoor positioning systems [5][6].

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In this paper, a ZigBee indoor positioning scheme based on the location fingerprinting approach is developed. The scheme includes four workflows: (1) Creation of location fingerprint table, (2) training of NN locating model, (3) data preprocess through the Signal-Index-Pair method, and (4) instant estimation of the mobile target's coordinate. In particular, the Signal-Index-Pair method is a data preprocess method that is proposed to enhance the precision of the NN locating model. Finally, based on the proposed scheme, we construct a prototype ZigBee indoor positioning system, tested in a gymnasium, to validate the effectiveness of the Signal-Index-Pair data preprocess method.

II. ZIGBEE INDOOR POSITIONING SCHEME

The developed ZigBee indoor positioning scheme using the Signal-Index-Pair data preprocess method is shown in Fig. 1, whose four workflows are sequentially described below.

2.1 Creation of Location Fingerprint Table

Assume that the positioning area is separated by a rectangular grid of *m* points, and the coordinate of each grid point is $\mathbf{P}_i = (x_i, y_i)$, $i = 1,2,...,m$. Also, *n* grid points are preset as the reference points, each equipped with a base station which is a ZigBee device. That is, there are a total of *n* base stations in the positioning area, and BS_j denotes the *j*th base station, $j = 1,2,...,n$.

First, the mobile target (MT) moves to the *i*th grid point whose coordinate is $\mathbf{P}_i = (x_i, y_i)$, and the ZigBee device on the MT begins to receive the signal sent by each base station. Let $rss^i_{BS_j}$ denotes the average RSS value, from the *j*th base station, at $\mathbf{P}_i$ during a pre-defined period of time. Then, the average RSS values from all of *n* base stations at $\mathbf{P}_i$ constitute the RSS vector $\mathbf{S}_i = (rss^i_{BS_1}, rss^i_{BS_2}, ..., rss^i_{BS_j}, ..., rss^i_{BS_n})$, which is called the location fingerprint associated with $\mathbf{P}_i$. Then, the ZigBee device on the MT sends the $\mathbf{S}_i$ over the air to the ZigBee coordinator which is connected to the positioning server. By repeating the above procedure until all of *m* grid points are visited, we can establish the location fingerprint table **LFT** associated with the positioning area in the positioning server. Note that the *i*th row of **LFT** is equal to the cascaded vector of $\mathbf{P}_i$ and $\mathbf{S}_i$, i.e. $\mathbf{LFT}_i = (\mathbf{P}_i, \mathbf{S}_i)$, $i = 1,2,...,m$.

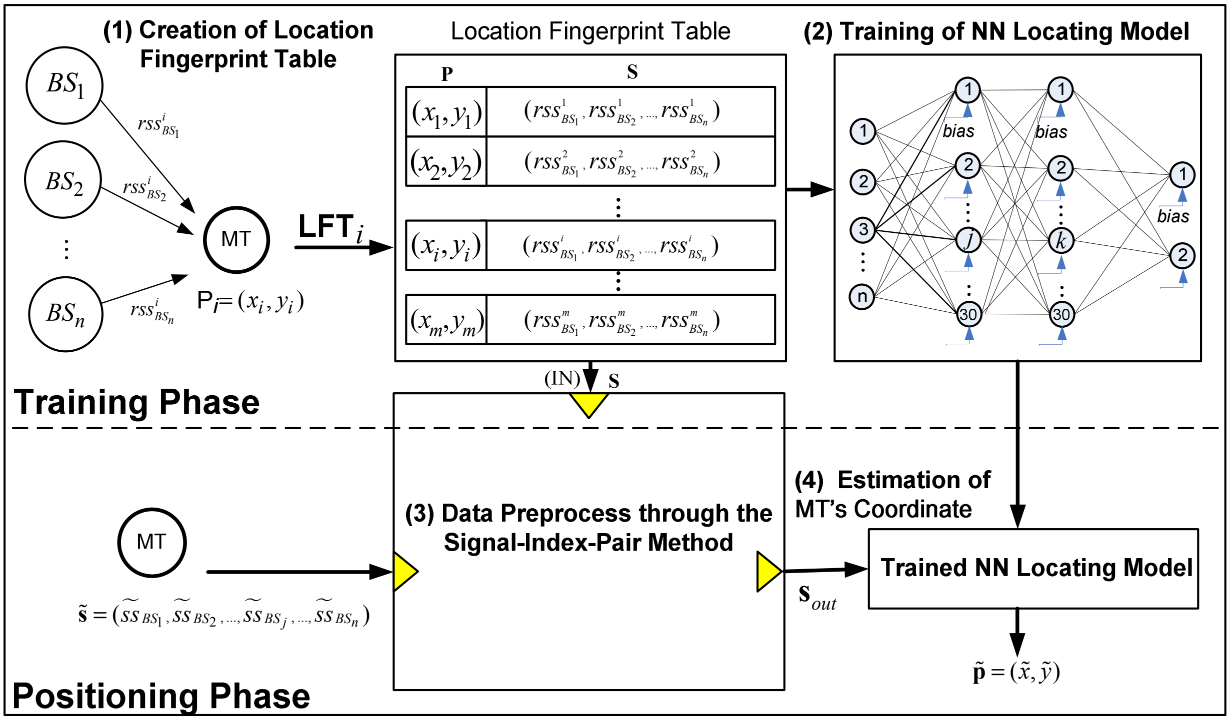

Fig. 1. ZigBee indoor positioning scheme using the signal-index-pair data preprocess method.

Take a gymnasium at Chung Cheng Institute of Technology, National Defense University, Taiwan, R.O.C., as a sample positioning area to illustrate the above workflow. The positioning area in the gymnasium is 29 meters long and 17 meters wide. The coordinate of the bottom-left corner is set as (0,0). The positive x-axis pointed rightwards from (0,0) along the horizontal line, while the positive y-axis points upwards from (0,0) along the vertical line. The scale interval on both axes is one meter. Therefore, the coordinate ranges of the x-axis and the y-axis are $0 \le x \le 17$ and $0 \le y \le 29$, respectively. The locations whose coordinate is a pair of integers are set as the grid points. Hence, the positioning area is covered by a rectangular gird of 540 grid points, i.e. m =540. Four base stations (BS1 to BS4), i.e. n =4, are set up at the locations (0,0), (0,29), (17,29), and (17,0), respectively. By the above-mentioned procedure, the location fingerprint table associated the grid points of such a setup is a 540 x 6 matrix, i.e. **LFT**=$[\mathbf{P}_{540\times 2} \quad \mathbf{S}_{540\times 4}]$.

2.2 Training of NN Locating Model

In the proposed positioning scheme, a neural network is used to establish the locating model. According to the results of various experimental tests and evaluations, the locating model of this research is constructed by a two-hidden-layer back propagation neural network (BPNN). The numbers of nodes in the input layer, the hidden layers, and the output layer are 4, 30, 30, and 2, respectively. The data in the location fingerprint table (**LFT**) are utilized to train the NN locating model. Specifically, the RSS matrix $\mathbf{S}_{540\times 4}$ of **LFT** are used as inputs, and the coordinate matrix $\mathbf{P}_{540\times 2}$ of **LFT** are the target outputs.

Each layer of the NN locating model is depicted as follows.

Input Layer:

There are four nodes in Input Layer. Their inputs are the RSS values, rss_{BS_1} to rss_{BS_4}, respectively.

Hidden Layer 1:

The activation function of each node in Hidden Layer 1 is the log-sigmoid function $f(x) = 1/(1+e^{-x})$.

Hidden Layer 2:

The activation function of each node in Hidden Layer 2 is also the log-sigmoid function $f(x) = 1/(1+e^{-x})$.

Output Layer:

There are two nodes in Output Layer, whose outputs correspond to the x coordinate and the y coordinate of the MT, respectively. The activation function of the nodes in Output Layer is the linear function $f(x) = x$.

For training the above BPNN, each row of the location fingerprint table, $\mathbf{LFT}_i = (\mathbf{P}_i, \mathbf{S}_i)$, $i = 1,2,...,540$, are sequentially used as the training data, with $\mathbf{S}_i$ being the input and $\mathbf{P}_i$ being the corresponding target output. During the training process, the weights are continuously updated by the gradient descent method. After the training process is completed, a trained NN locating model for the positioning area is obtained. Then, by inputting a sample RSS vector of the MT into the trained NN locating model, the outputs will be the estimation of the MT's coordinate.

2.3 Data Preprocess through the Signal-Index-Pair Method

As mentioned previously, the RSS value of the MT at the same location may vary over time. Therefore, if a raw RSS vector of the MT is directly inputted into the trained NN locating model, the estimation precision of the MT's coordinate may be very poor. To enhance the precision of the positioning system based on NN locating model, a data preprocess method, called Signal-Index-Pair method, is proposed. The functional blocks of the Signal-Index-Pair method, including (1) Creation of Index-Pair Lookup Table (**IPLT**) and (2) Signal Replacement, are shown in Fig. 2, which is described below.

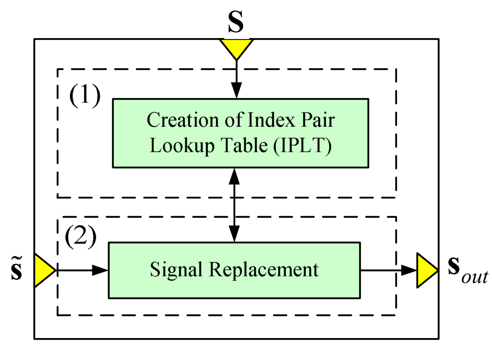

Fig. 2. Functional blocks of the Signal-Index-Pair data preprocess method.

A. Creation of Index Pair Lookup Table (IPLT)

The purpose of creating the **IPLT** is to establish a feature for each RSS vector $\mathbf{S}_i$ in **LFT**. If the largest value and the second largest value in a RSS vector are the *p*th element and the *q*th element of the RSS vector, respectively, then the index pair (*p*,*q*) is defined as a feature of that RSS vector. The process of creating the Index Pair Lookup Table (IPLT) associated with the **LFT** is shown in Fig. 3 and explained as follows.

Step (1): Initially, set *i*=1.

Step (2): Sort the RSS vector $\mathbf{S}_i$ in descending order.

Step (3): Pick the first number N_1 and the second number N_2 of the sorted $\mathbf{S}_i$. Then, N_1 and N_2 are the largest value and the second largest value in the original $\mathbf{S}_i$, respectively.

Step (4): Find out the index (= p_i) of N_1 in the original $\mathbf{S}_i$.

Step (5): Find out the index (= q_i) of N_2 in the original $\mathbf{S}_i$.

Step (6): Store the index pair (p_i, q_i) in the *i*th row of the **IPLT**, i.e. $\mathbf{IPLT}_i = (p_i, q_i)$.

Step (7): Increment *i*, i.e. $i = i + 1$.

Step (8): If all of $\mathbf{S}_i$ in **LFT** have been processed, i.e. $i > m$, then the process ends. Otherwise, Steps (2) to (8) are repeated.

For the sample positioning area in the gymnasium, the dimension of the RSS matrix **S** is 540×4. The generated **IPLT** by the process in Fig. 3 is a 540×2 matrix.

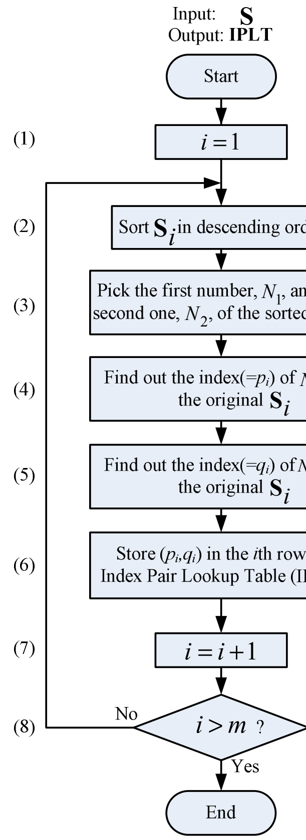

Fig. 3. The process of creating the Index Pair Lookup Table associated with the LFT.

B. Signal Replacement

When a sample RSS vector $\tilde{\mathbf{s}}$ is collected by the MT in the positioning phase, the feature of $\tilde{\mathbf{s}}$, an index pair, will be computed first. If the index pair of $\tilde{\mathbf{s}}$ is equal to at least one row of **IPLT**, then $\tilde{\mathbf{s}}$ will be replaced by the RSS vector $\mathbf{S}_i$ under the condition that $\mathbf{S}_i$ has the same feature as $\tilde{\mathbf{s}}$, and the Euclidean distance between $\mathbf{S}_i$ and $\tilde{\mathbf{s}}$ is minimum. The signal replacement process for a sample RSS vector is shown in Fig. 4 and depicted as follows.

Step (1): Initially, set $i = 1$, $\mathbf{s}_{out} = \tilde{\mathbf{s}}$, and $d_s = 100$, where $\tilde{\mathbf{s}}$ is a sample RSS vector collected by the MT, $\mathbf{s}_{out}$ is the output RSS vector generated by the Signal-Index-Pair method, and d_s is a dummy variable to temporarily store the Euclidean distance.

Step (2): Compute the index pair $(\tilde{p}, \tilde{q})$ of $\tilde{\mathbf{s}}$ using the Steps (2) to (5) in Fig. 5.

Step (3): If $(\tilde{p}, \tilde{q})$ is equal to the *i*th row of the **IPLT,** i.e. $(\tilde{p}, \tilde{q}) == \mathbf{IPLT}_i$, then proceed to Step (4). Otherwise, go to Step (7).

Step (4): Compute the Euclidian distance $d(\tilde{\mathbf{s}}, \mathbf{S}_i)$ between $\tilde{\mathbf{s}}$ and $\mathbf{S}_i$ in **LFT**.

Step (5): If $d(\tilde{\mathbf{s}},\mathbf{S}_i)$ is less than d_s, indicating that $\mathbf{S}_i$ is closer to $\tilde{\mathbf{s}}$ than other RSS vectors, then proceed to Step (6). Otherwise, go to Step (7).

Step (6): Set $d_s = d(\tilde{\mathbf{s}},\mathbf{S}_i)$ and $\mathbf{s}_{out} = \mathbf{S}_i$.

Step (7): Increment i, i.e. $i = i+1$.

Step (8): If all of the rows in **IPLT** have been compared with the index pair of $\tilde{\mathbf{s}}$, i.e. $i > m$, then the process ends and $\mathbf{s}_{out}$ is obtained. Otherwise, Steps (3) to (8) are repeated. Here, m is equal to 540.

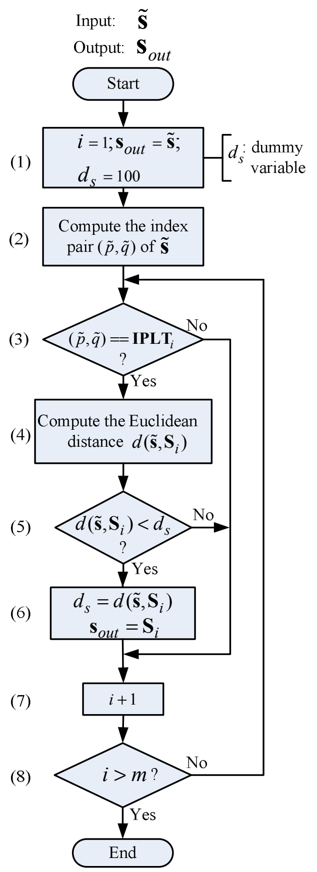

Fig. 4. The signal replacement process for a sample received signal strength vector.

2.4 Instant Estimation of the MT's Coordinate

Once the $\mathbf{s}_{out}$ generated by the Signal-Index-Pair method is obtained, $\mathbf{s}_{out}$ is instantly inputted into the trained NN locating model. Then, the output of the trained NN locating model is the estimated coordinate of the MT, $\tilde{\mathbf{p}} = (\tilde{x},\tilde{y})$.

III. TESTING RESULTS AND PERFORMANCE EVALUATION

Based on the proposed ZigBee indoor positioning scheme shown in Fig. 1, a prototype ZigBee indoor positioning system is developed and deployed in a gymnasium at Chung Cheng Institute of Technology, National Defense University. The implementation and the testing results of the prototype ZigBee positioning system is depicted in this section. Firstly, the construction of the prototype ZigBee indoor positioning system is described. Secondly, evaluation methods for the positioning accuracy and precision are described. Then, three locating algorithms, other than neural network [7][8], used for comparison are introduced. Finally, the testing results are presented.

3.1 Construction of Prototype ZigBee Indoor Positioning System

For the system implementation in the positioning server, we use Microsoft Windows 2000 as the development platform, Microsoft .NET CLR as the runtime environment, and Microsoft SQL Server 2000 to create the database. The system programs are written in C#, ASP.NET, and ADO.NET, while Visual Studio .NET is the programming tool. Besides, Z-Profile Builder, Programmer's Notepad 2, and Atmel AVR Studio are employed to develop the software used in the ZigBee devices.

Regarding to the hardware requirement, a PC is needed to be the positioning server. The TI/Chipcon's ZigBee modules are used as the ZigBee devices. To implement the function of remote monitoring, a high-speed spherical Web camera is utilized to instantly show the images of the monitoring (positioning) area.

3.2 Evaluation of Location Estimation Accuracy and Precision

Usually, a location estimation accuracy, or called positioning accuracy, is described by the error distance deviated from the actual location, while a location estimation precision, or called positioning precision, is described in percentages of location estimation errors that are within the distance of accuracy. In this work, the accuracy of the positioning system is measured by the Euclidean distance between the estimated coordinate $\tilde{\mathbf{p}}$ and the actual coordinate $\mathbf{P}$, i.e. the error distance between $\tilde{\mathbf{p}}$ and $\mathbf{P}$ computed by $d(\tilde{\mathbf{p}},\mathbf{p}) = \|\tilde{\mathbf{p}} - \mathbf{p}\|$. The smaller the error distance is, the higher the positioning accuracy.

On the other hand, the precision of the positioning system is measured by the cumulative error probability (*CEP*) of the estimated coordinates. The pseudo code for computing the *CEP* is shown in Fig. 5 and explained below. Assume that there are a total of *m* tested locations, and $\mathbf{P}$ is the actual coordinates matrix whose dimension is $m \times 2$, while $\tilde{\mathbf{p}}$ is corresponding estimated coordinates matrix whose dimension is also $m \times 2$. First, compute the error distance $\mathbf{e}(i)$ by the Euclidean distance between $\mathbf{P}_i$ and $\tilde{\mathbf{P}}_i$, where $\mathbf{P}_i$ is the *i*th row of $\mathbf{P}$, $\tilde{\mathbf{P}}_i$ is the *i*th row of $\tilde{\mathbf{p}}$, and $i = 1,2,...,m$. Then, find the smallest integer *M* bigger than the maximum of the error distance vector $\mathbf{e}$ by $M = Ceil(\max(\mathbf{e}))$. Next, the index *j* is increased from one meter to *M* meters, with an interval of one meter. For each *j*, calculate *C*, the number of tested locations whose error distance is less than or equal to *j*. Then, the cumulative error probability within *j* meter can be obtained by $CEP(j) = C/m$.

Inputs:
m : total number of tested locations,
P: actual coordinates matrix of tested locations , $m \times 2$,
$\tilde{\mathbf{p}}$: estimated coordinates matrix of tested locations, $m \times 2$.
Output:
CEP: Cumulative Error Probability.

for i =1 to m
$\mathbf{e}_i = \|\mathbf{P}_i - \tilde{\mathbf{P}}_i\|$;
end for
$M = Ceil(\max(\mathbf{e}))$;
for j =1 to M
C =0;
for i =1 to m
if ($\mathbf{e}_i \le j$)
$C = C + 1$;
end if
end for
$CPF(j) = C / m$;
end for

where
$\| \cdot \|$: Euclidean distance between two vectors
max(): the maximum value of a vector
$Ceil(x)$: the smallest integer bigger than x

Fig. 5. Pseudo code for computing the positioning cumulative error probability (*CEP*).

3.3 Other Locating Algorithms Used for Comparison

A. Minimum Euclidean Distance (MED) method [9]

The Euclidean distance $d(\mathbf{x},\mathbf{y})$ between the vector $\mathbf{x} = (x_1, x_2, \cdots, x_n)$ and the vector $\mathbf{y} = (y_1, y_2, \cdots, y_n)$ is computed as follows:

$$d(\mathbf{x},\mathbf{y}) = \|\mathbf{x} - \mathbf{y}\| = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \tag{1}$$

Given a sample RSS vector $\tilde{\mathbf{s}}$, the corresponding estimated coordinate $\tilde{\mathbf{p}} = (\tilde{x}, \tilde{y})$ by the minimum Euclidean distance (MED) method is the location vector $\mathbf{P}_i = (x_i, y_i)$ in **LFT,** whose associated RSS vector $\mathbf{S}_i$ is nearest to $\tilde{\mathbf{s}}$ in terms of Euclidean distance.

B. K Nearest Neighbor (KNN) method [10]

In the k nearest neighbor (KNN) method, the k location vectors in **LFT,** whose associated RSS vectors are nearest to $\tilde{\mathbf{s}}$ in terms of Euclidean distance, are found first. Then, the estimated coordinate $\tilde{\mathbf{p}} = (\tilde{x}, \tilde{y})$ by the KNN method is the average of these location vectors:

$$\tilde{\mathbf{p}} = (\tilde{x}, \tilde{y}) = \frac{\sum_{i=1}^{k} \mathbf{p}_{KNN}(x_i, y_i)}{k} \tag{2}$$

where $\mathbf{p}_{KNN}(x_i, y_i)$ is the *i*th one of the k location vectors found by the KNN method. When k is equal to one, the KNN method is the same as the MED method.

C. Weighted K Nearest Neighbor (WKNN) method [11]

In the weighted k nearest neighbor (WKNN) method, the k location vectors in **LFT,** whose associated RSS vectors are nearest to $\tilde{\mathbf{S}}$ in terms of Euclidean distance, are found first. Then, the estimated coordinate $\tilde{\mathbf{p}} = (\tilde{x}, \tilde{y})$ by the WKNN method is computed as follows:

$$\tilde{\mathbf{p}} = (\tilde{x}, \tilde{y}) = \frac{\sum_{i=1}^{k} \frac{\mathbf{p}_{KNN}(x_i, y_i)}{d(\tilde{\mathbf{s}}, \mathbf{S}_k^i) + d_0}}{\sum_{i=1}^{k} \frac{1}{d(\tilde{\mathbf{s}}, \mathbf{S}_k^i) + d_0}} \tag{3}$$

where $\mathbf{S}_k^i$ is the RSS vector of the *i*th one of the k location vectors, $d(\tilde{\mathbf{s}}, \mathbf{S}_k^i)$ is the Euclidean distance between $\tilde{\mathbf{S}}$ and $\mathbf{S}_k^i$, and d_0 is a small number, such as 0.01dBm, to avoid division by zero.

3.4 Test Results

To evaluate the performance of the proposed positioning scheme, 250 locations in the gymnasium are selected to collect 250 sample RSS vectors, one for each location, for the tests. For comparison, six locating methods are employed, including (1) 1NN: *1* nearest neighbor method (equivalent to the minimum Euclidean distance method), (2) 5NN: *5* nearest neighbor method, (3) W2NN: weighted *2* nearest neighbor method, (4) W5NN: weighted *5* nearest neighbor method, (5) 4-30-30-2 BPNN: a two-hidden-layer back propagation neural network with 4 nodes, 30 nodes, 30 nodes, and 2 nodes in the input layer, the first hidden layer, the second hidden layer, and the output layer, respectively, and (6) 4-30-30-2 SIP-BPNN: 4-30-30-2 BPNN with data preprocess by the proposed Signal-Index-Pair (SIP) method.

The positioning cumulative error probabilities (CEPs) of the six locating methods are shown in Fig. 6. The positioning error distances in meters at CEP=25%, CEP=50%, and CEP=75% are also presented in Table 1. As shown in the figure, the proposed SIP-BPNN method clearly enhances the positioning precision of the BPNN method. It also has higher positioning precision than other locating methods.

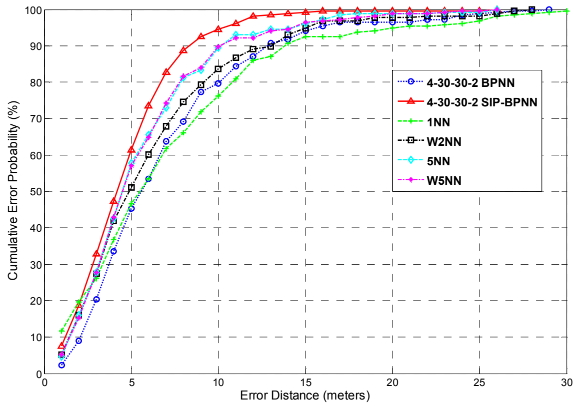

Figure 6. Positioning cumulative error probabilities (CEPs) of the six locating methods.

Table 1. Positioning error distances at CEP=25%, CEP=50%, and CEP=75% of the six locating methods.

Methods	CEP=25%	CEP=50%	CEP=75%
BPNN	3.354m	5.574m	8.714m
1NN	2.825m	5.505m	9.732m
5NN	2.767m	4.488m	7.240m
W2NN	2.793m	4.875m	8.087m
W5NN	2.781m	4.500m	7.106m
BPNN with SIP	2.452m	4.203m	6.176m

IV. Conclusion

In this paper, an indoor positioning scheme based on ZigBee's received signal strength (RSS) is developed. First, the location fingerprint table (**LFT**) associated with the positioning area is created. The fingerprint of a location refers to the vector of RSS values at that location. The **LFT** comprises all the location fingerprints and the corresponding location coordinates of the pre-selected points in the positioning area. Second, a two-hidden-layer BPNN is trained by the data of **LFT** to be the locating model. Third, the Signal-Index-Pair (SIP) method is proposed to preprocess the sample RSS vector that is collected in the positioning stage and will be inputted into the NN locating model for estimating the coordinate of the mobile target.

A prototype ZigBee indoor positioning system based on the developed scheme is constructed and deployed in a gymnasium for conducting tests. The testing results show that within the error distance of 5 meters, the BPNN with the SIP method has 17% CEP (cumulative error probability that is defined as the positioning precision in this research) improvement over the original BPNN method. It also achieves 5% CEP higher than the *k*NN (*k*=5) method and the W*k*NN (*k*=5) method. The test results demonstrate that the proposed scheme can be utilized to develop ZigBee indoor positioning systems, and the SIP method can effectively enhance the precision of ZigBee indoor positioning. Potential applications include patient tracking in hospitals, object tracking for factory monitoring, self-navigation of autonomous robots, and visitors monitoring in military buildings, and so on.

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