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SIMPLE YET EFFECTIVE INTELLIGENT INDOOR POSITIONING SYSTEM

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Abstract. *Seeing that GPS fails to function inside a building, indoor positioning system (IPS) has recently gained much attention in the field of rescue, medical application, public facilities, emerging indoor location based services, etc. This study proposes a novel strategy based on wireless sensor network (WSN) to achieve high positioning accuracy for moving entities. Firstly, radial basis function network (RBFN) model for indoor location estimation is constructed in an unknown environment. Secondly, owing to the shortcoming of locating instant received signal strength (RSS), we introduce the benefits of using the average RSS to reduce noise interference and exclude transient APs. In addition, we integrate ZigBee hardware to realize a set of convenient wireless IPS with comparatively low cost. Finally, in order to reach an optimal accuracy, we adopt multiple similar networks within the same environment. Experiments in this study have demonstrated effective enhancement of existing IPS accuracy with the average error as little as 2.8 meters 100% when compared with other approaches.*
Keywords: Indoor positioning system, Wireless sensor network, RBFN, ZigBee

1. **Introduction.** Recently, the applications of wireless sensor network (WSN) have been widely discussed. The WSN is a kind of wireless communication technology for information detection of surrounding environment by a distributed network composed of a huge number of wireless sensors with low power consumption and low cost through self-organized communication [1-3,7,11,13,20,22,31,33,34,36]. It can be applied to various fields including biological information, military battle field, industrial control, intelligent building, and family care [8,9,16,19,28,30-32,34]. However, among numerous applications of wireless sensor network, since sensors must first identify their own positions, the research on positioning issue then becomes a hot topic [4-7,10]. More attention has been drawn to the indoor positioning system (IPS) of intelligent robot in recent years [24]. The robots can be sent out for exploring, searching, mapping and rescuing (such as nuclear power plant disaster in Fukushima, Japan, 2011) in unknown indoor environment to avoid direct human encountering with unidentified danger. The most well known outdoor positioning technology is the GPS; nevertheless, there must be direct line-of-sight between satellite and receiver [1,15,22,30]. For indoor positioning by WSN technology, several sensors with fixed known positions will be set up for calculating the positions of receiving nodes. There are two popular methods for radio frequency identification (RFID): range-based positioning and range-free positioning calculation [30]. RFID is a passive device mainly for shorter distance positioning, and it requires robots to have additional built-in readers while being close to the target (with Tag). Bluetooth is similar to RFID in terms of the service for small region, whereas ZigBee provides mid-range sensing with low cost, low power, low complexity, and high scalability. Nowadays, many positioning techniques

have been incorporated in wireless network including Time of Arrival (TOA), Time Difference of Arrival (TDOA), Angle of Arrival (AOA), DOA [1,2,38], and "Received Signal Strength" (RSS) [20-22,33]. Since the positioning system based on the design following IEEE 802.11 standard usually consumes more electricity, it is not the optimal solution for long-term tracking, such as logistic management or intelligent housing. Also, the positioning accuracy will also be directly affected by the number of receiving nodes such that it is costly [20]. This study aims at constructing a set of robot IPS with certain accuracy. The focus will be on the utilization of ZigBee network with low power consumption and high scalability, and RSS measurement techniques, where the collection of sensed wireless signal strength is completed by using the chip's own function in conjunction with RBFN network for RSS positioning. As indicated by the experiments, an average positioning error of 1.47 meter 90% can be obtained when the position estimation has been conducted based on multiple RBFN, and the overall average error is within the range of 2.8 meters 100%.

The structure of this paper is as follows. The related knowledge and the proposed system structure have been introduced in Section 2 and Section 3. In Section 4 the experimental results and comparison analysis are discussed, while the conclusion can be found in Section 5.

2. Preliminaries.

2.1. Positioning technologies.

The frequently used IPS are Infra-red (IR), Ultra Sonic, and wireless local area network (WLAN), and the comparisons are as shown in Table 1.

TABLE 1. Comparison of indoor position localization technique

	Principle	Advantages/Disadvantages
IR	Measured distance is calculated from the arrival time of received reflection.	Susceptible to sunlight interference and accuracy due to small emission angle.
Ultra Sonic	After ultra sonic wave is emitted, the different cross-sections reflection from objects will be observed.	Susceptible to environmental interference.
WLAN	Position estimation based on the T/R of wireless signals (RFID & Bluetooth)	Wireless signal is susceptible to interference from obstructions.

There are four frequently used technologies: AOA, TOA, TDOA, and RSS (Kegen, 2009). AOA is to determine the position of moving target according to the angle direction of arrived signal as shown in Figure 1.

However, AOA relies heavily on the directional precision that greatly increased cost. TOA is mainly the calculation of distance between the detected target and the base according to signal transmission time, and the detected target using algorithm as shown in Figure 2.

With the TDOA method, two signals with different transmission speeds are transmitted from transmitting nodes simultaneously, and then the calculation of distance between these two nodes is conducted as shown in Figure 3. Time synchronization is necessary for both TDOA and TOA techniques. However, the advantage of TDOA is the use of relative time of arrival instead of the absolute time of arrival (TOA) for error reduction. And the disadvantage is the need for additional extra T/R device.

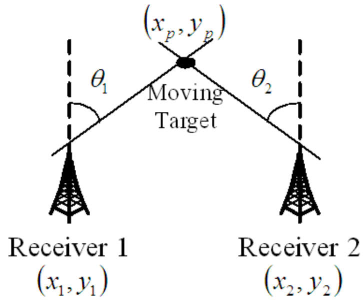


Figure 1. AOA localization configuration

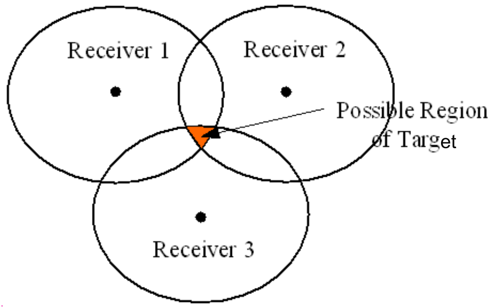


Figure 2. TOA localization configuration

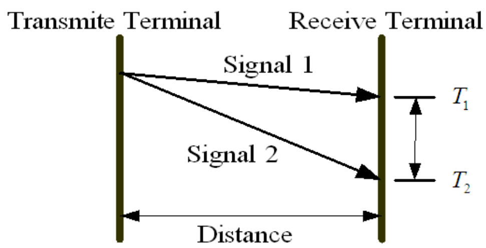


Figure 3. TDOA localization configuration

RSS by multiple receiving nodes from transmission nodes are used for determination of the distance between receiving node and transmitting node.

2.2. **Zigbee and structure.** Power supply for sensor installation is crucial for wireless network especially for the demand for installations of large amount of sensors in outdoor environment. This is how the Zigbee was born as a wireless network technology with low cost, and low power consumption. The IEEE 802.15.4 standard protocol is shown in Figure 4 (Lu, 2008) [18].

2.2.1. *Network topology.* In terms of software function, network nodes can be categorized as PAN Coordinator, Coordinator, and End Device as described in Table 2.

IEEE 802.15.4 provides three basic types of network topologies as Figure 5.

2.2.2. *Software structure.* There are two layers in the software configuration within node of IEEE 802.15.4 as Figure 6.

Interactions among applications are conducted through the Stack API and the Stack Layers of IEEE 802.15.4. The interactive access to hardware registers by applications is conducted through integrated peripheral equipment API and integrated on-chip peripheral equipment. In hardware layer all kinds of interruptions can be generated and sent to every software module through interruption control codes. In addition, the following features can be used for software design (1) Clear Channel Assessment (CCA), (2) Link Quality Indicator (LQI). LQI value is larger than RSS value such that it has higher resolution.

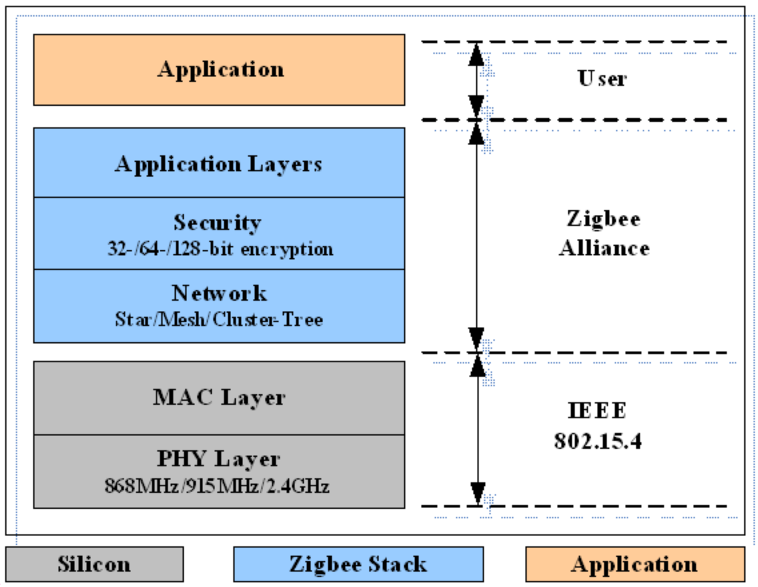
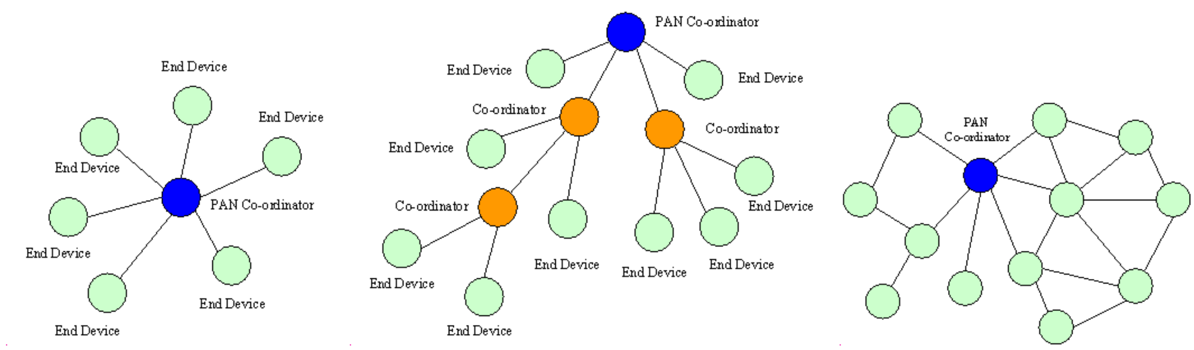


FIGURE 4. IEEE 802.15.4/Zigbee protocol and structure

TABLE 2. Node function

	Software Function of Node	Node Type
PAN Coordinator	Assign the PAN ID to network, and manage.	FFD
	Frequency searching and assignment.	
	Connect ability with other device.	
	Routing ability.	
	Package reception and transmission.	
Coordinator	Connect ability with other device.	FFD
	Routing ability.	
	Package reception and transmission	
End Device	Connect with PAN Coordinator/Coordinator	FFD/RFD
	Package reception and transmission.	



(a) Star topology (b) Tree topology (c) Mesh topology

FIGURE 5. Network topology

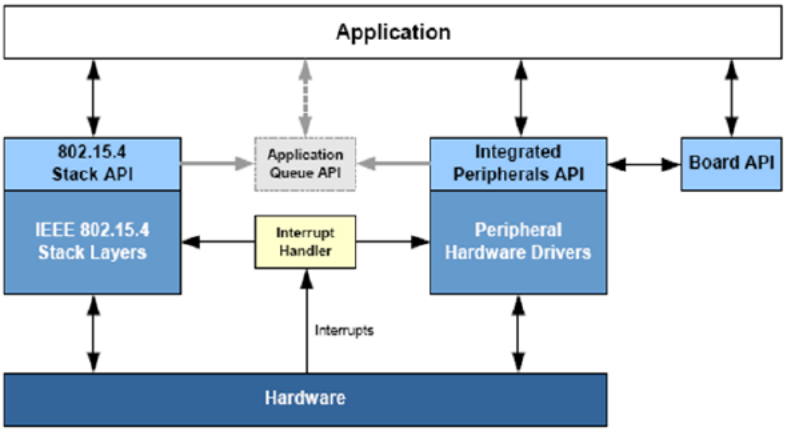


FIGURE 6. Basic software configuration of IEEE802.15.4

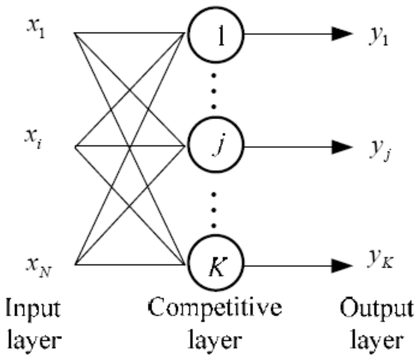


FIGURE 7. Competition learning network [35]

2.3. **NN algorithm.**

– ***Competitive learning algorithm***

Neural network has the information processing capability similar to biological neurons. It allows to resolve the nonlinear problems. The single layer neural network based on competitive learning algorithm [27] is as shown in Figure 7. This learning algorithm is usually used for cluster analysis, which is to figure out the structure and cluster relationship of data itself with no prior classification information. If we assume that the Nth dimension input can be represented by X:

$$X = [x_1, x_2, \cdots, x_N]^T \tag{1}$$

The weight vector of the jth artificial neuron is as shown in (2):

$$w_j = [w_{j1}, w_{j2}, \cdots, w_{jN}]^T \qquad j = 1, 2, \cdots, K \tag{2}$$

where K is the number of selected neurons. The learning algorithm is as shown below:

Step 1. Competitive phase: Winner is selected.

The artificial neuron with the smallest Euclidean distance between input vector X and weight vector w_j is the winner as shown in (3):

$$d(X) = \min_j \|X - w_j\|, \ j = 1, 2, \cdots, K \tag{3}$$

Step 2. Reward phase: The weight vector of winner is adjusted.

$$w_j(n+1) = w_j(n) + \eta(X - w_j(n)) \tag{4}$$

where η and n are the number of iterations of learning speed and learning process.
Step 3. Iteration phase: If the number of iterations has reached the preset upper limit, the training must be stopped. Otherwise, the training will be resumed from competitive phase.

– ***Radial basis function network*** (RBFN)

The RBFN is a typical multi-layer feed-forward network with rapid learning capability [27]. In Figure 8 there is a three-layer RFBN network including input layer, hidden layer and output layer. Suppose the input dimension as p and the number of neurons in hidden layer as J, then the network output can be shown as:

$$F\left(\underline{x}\right) = \sum_{j=1}^{J} w_j \varphi_j\left(\underline{x}\right) + \theta = \sum_{j=0}^{J} w_j \varphi_j\left(\underline{x}\right) \tag{5}$$

where $\underline{x}$ represents input vector, w_j represents the weight value from the jth neuron in hidden layer to the artificial neuron in output layer, $\theta = w_0$ represents adjustable offset, and $\varphi_j\left(\underline{x}\right)$ represents the basis function of output value of the jth neuron in hidden layer, which is a Gaussian function with definition as shown in (6):

$$\varphi_j\left(\underline{x}\right) = \exp\left(-\frac{\left\|\underline{x} - \underline{m}_j\right\|^2}{2\sigma_j^2}\right) \tag{6}$$

where J represents the number of artificial neurons in hidden layer, $\underline{m}_j$ represents the center position of the jth Gaussian function, and σ_j represents the standard error of the jth Gaussian function.

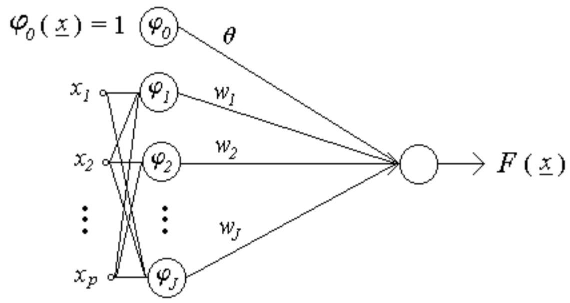


Figure 8. RBFN structure

Two phases are included in the RBFN. The learning of nodes in hidden layer is mainly about using non-supervision for adjusting the adjustable parameters $\underline{m}_j$ and σ_j, while output nodes are adjusted by supervision method adoption of LMS for network parameters.

$$E(n) = \frac{1}{2}\left(y_n - F\left(\underline{x}_n\right)\right)^2 \tag{7}$$

where $F\left(\underline{x}_n\right)$ is the nth output value, and y_n represents the expected output of the nth input data. According to the selected basis function as (6), the adjustment equations for $\underline{w}$, $\underline{m}_j$ and σ_j are derived as:

$$\underline{w}(n+1) = \underline{w}(n) + \eta\left(y_n - F\left(\underline{x}_n\right)\right) \cdot \underline{\varphi}\left(\underline{x}_n\right) \tag{8}$$

$$\underline{m}_j(n+1) = \underline{m}_j(n) + \eta\left(y_n - F\left(\underline{x}_n\right)\right) \cdot w_j(n) \cdot \underline{\varphi}\left(\underline{x}_n\right) \cdot \frac{1}{\sigma_j^2}\left(\underline{x}_n - \underline{m}_j(n)\right) \tag{9}$$

$$\sigma_j(n+1) = \sigma_j(n) + \eta\left(y_n - F\left(\underline{x}_n\right)\right) \cdot w_j(n) \cdot \underline{\varphi}\left(\underline{x}_n\right) \cdot \frac{1}{\sigma_j^2}\left\|\underline{x}_n - \underline{m}_j(n)\right\|^2 \tag{10}$$

where η is learning rate, meanwhile

$$\underline{\varphi}(\underline{x}_n) = \left[\underline{\varphi}_0(\underline{x}_n), \underline{\varphi}_1(\underline{x}_n), \cdots, \underline{\varphi}_J(\underline{x}_n)\right]^T \tag{11}$$

$$\underline{\varphi}_0(\underline{x}_n) = 1 \tag{12}$$

and

$$\underline{w}(n) = [\theta(n), w_1(n), \cdots, w_J(n)]^T \tag{13}$$

3. The Proposed IPS Designation.

3.1. **Concept.** The **IPS** proposed is designed by integrating the Zigbee, and the RBFN estimation algorithm is used for achieving the required accuracy. First, RBFN is used for conducting model of environment. It is divided into offline and real time phase. Offline phase includes setting of experimental environment, selection of sampling points, and measurement. Real time phase is all about the follow-up verification. The architecture is as shown in Figure 9.

The positioning method as shown in Figure 10 by first placing three sensors with known positions in indoor environment, and then the strength of signal sent from sensor to target (robot) is used to estimate the position of robot.

3.2. **Pre-processing for received signal.** Basically, signals transmitted from sensor nodes must be received for a period of time. In other words, signal measurement is susceptible to environmental effects such as people walking. The effects of these interference factors can be reduced by adopting pre-processing of received signal (value in the box) as Figure 11.

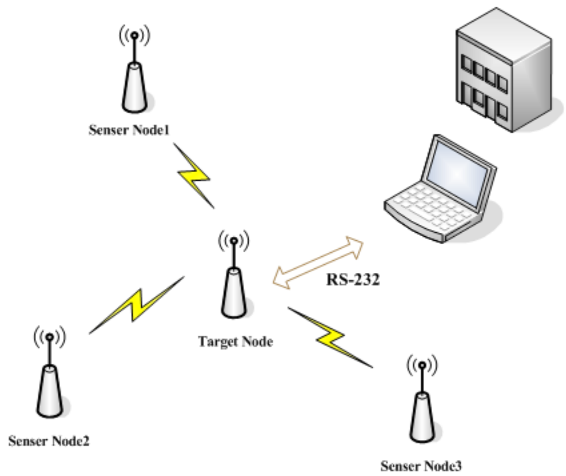


FIGURE 9. The proposed localization configuration of ZigBee

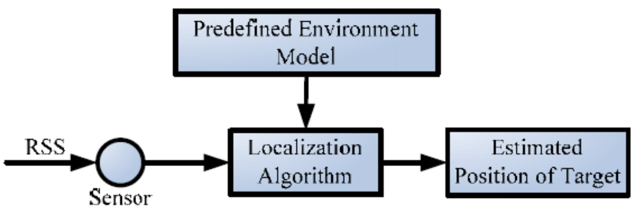


FIGURE 10. RSSI localization configuration

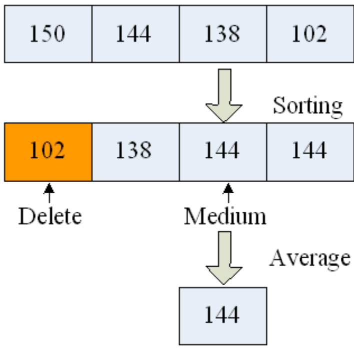


FIGURE 11. ZigBee signal pre-processing

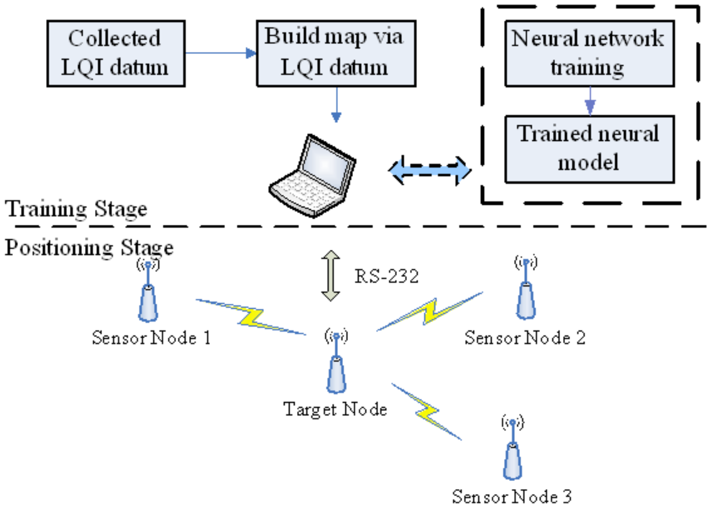


FIGURE 12. The proposed system function block diagram

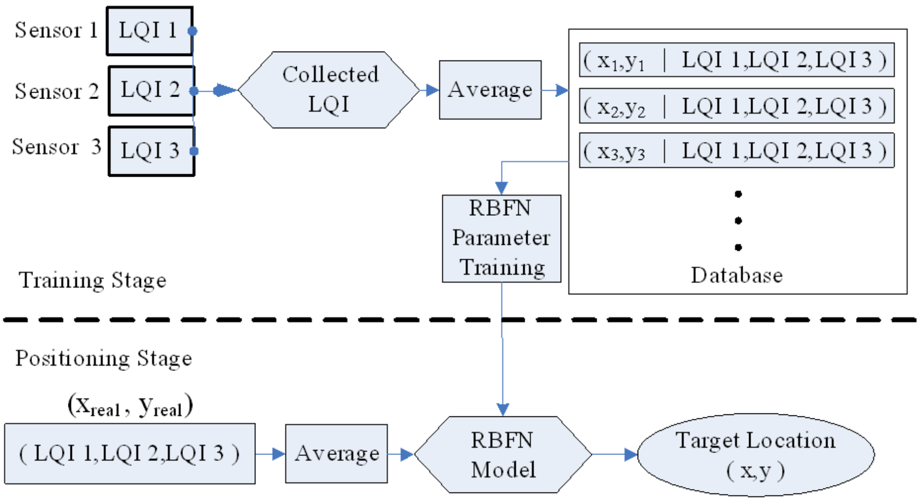


FIGURE 13. Data flow and processing

3.3. **Overall system.** The ZigBee development kit FT-6200 developed by Fontal has been adopted for measuring LQI, and the estimated algorithm is RBFN. The complete system is Figure 12.

The positioning procedure can be divided into two stages. (1) The averaging LQI values of environmental will be collected. Then it can be input into RBFN for training. The cluster classification is conducted for all LQI values in the database through competitive learning to define the parameters of RBFN. (2) The real time LQI values will be thrown into the trained RBFN for verification as shown in Figure 13.

3.4. **RBFN-based IPS algorithm.**
– ***Competitive learning algorithm***
The competitive learning here is to find similar characteristics and relationships among unmarked sample sets for identifying the cluster center vector of the training samples. The inputs in Figure 13 are $(x, y|QI1, LQI2, LQI3)$, where (x, y) represents the coordinates of the point to be measured. Follow the similar steps as Subsection 2.3. The number of neurons is set in hidden layer and the sample is selected in Figure 8, where

$$X = [LQI1, LQI2, LQI3]^T \tag{14}$$

In addition, the cluster center vector of initial configuration is selected from input training for the first time. The winning neuron in hidden layer is calculated by (3). The weight vector of the winning neuron is adjusted by (4). The calculated cluster center vector $\underline{m}_j$ and standard deviation σ_j are then saved for the configuration of RBFN.
– ***RBFN***
The training step of RBFN model for localization in Figure 8 is as follows:

Step 1: The result of competitive learning algorithm is used for initiating the cluster center vector $\underline{m}_j$ and standard deviation σ_j of RBFN. The weight vector $\underline{w}$, learning rate is η, and convergence conditions are also set. A proper initialization of RBFN are given as 6000 iteration, 1 output, 3 hidden neuron, 3 input vector, and initial weights with $-1 \sim 1$.
Step 2: In this feed-forward phase, the input training sample is sent into the network during the nth learning such that the output of this learning can be calculated.
Step 3: In this back propagation phase, calculation of mean square error of expected outputs of network outputs is conducted.
Step 4: The parameters of RBFN such as $\underline{w}$, $\underline{m}_j$, σ_j and θ are adjusted simultaneously in the opposite direction of the gradient of mean square function.
Step 5: Check whether or not the convergence conditions have been met. Otherwise, it will go back to Step 2 for continued training.
Step 6: Output of the estimated coordinates of target.

Noted the number of vector centers is determined based on the number of inputs. It is shown that the trained artificial neural network will perform better.

3.5. **Experimental statistics.** The selected experimental environment is a 7.26m $\times$ 16.5m rectangular space on the third floor of Engineering Building I of Chung Hua University as Figure 14, where $S1$, $S2$, $S3$ are the transmission nodes, and white and red nodes are the nodes of target measurement and testing. In this experiment the field measurement is adopted for constructing the required database, while random distribution sampling approach has been conducted, and 49 target nodes are selected for LQI. 5 LQI values from 3 transmission nodes will be recorded for each node to establish the database of this site, where 38 white nodes selected from the 49 nodes of moving target are used as sampling nodes for the training of RBFN. Two strategies are proposed. Strategy 1: A single network is given for whole environment. Strategy 2: The experimental environmental will be divided into four independent areas and multiple neural networks will be

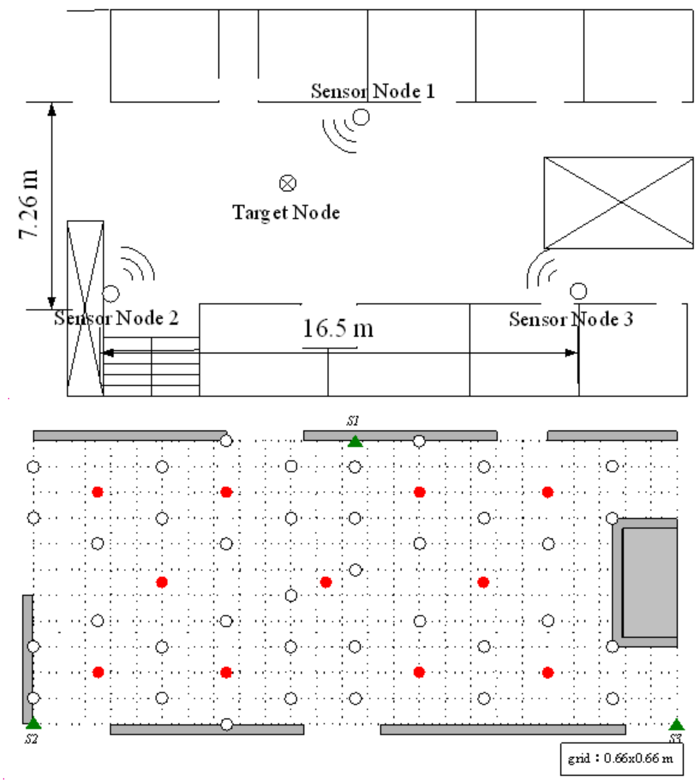
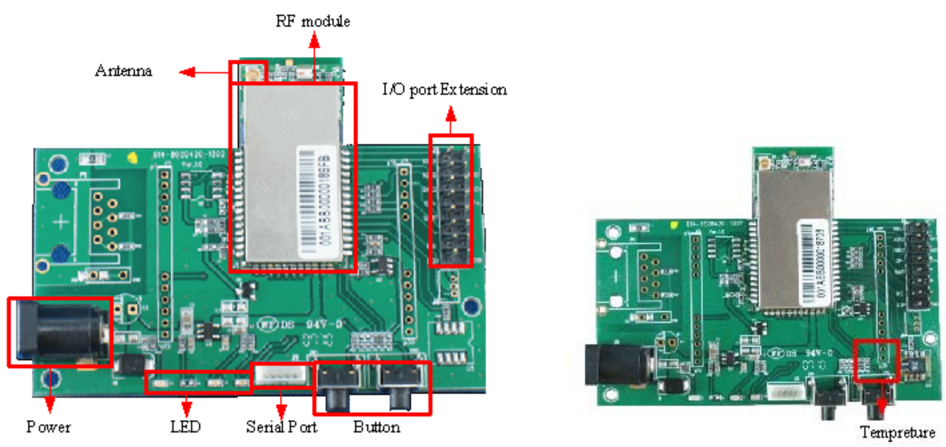


FIGURE 14. The test and verification environment node

used. After the establishment of network, the remaining 11 red nodes from database will be used as the tested nodes.

3.6. **Software/Hardware implementation.** FT-6200 kit includes FT-6250 and FT-6251 as Figure 15 with 32-bit RISC compatible, 2.4GHz IEEE 802.15.4 communication protocol, and 64kB ROM and 96kB RAM. Development platform developed by Jennic is used for program development.

For FT-6250/FT-6251, data is not transmitted to each other at any time among all nodes. Instead, the polling approach is adopted. When the Coordinator as an unknown



(a) FT-6250 (b) FT-6251

FIGURE 15. FT-6250/FT-6251 hardware

node has assigned certain End Device (as a known node) to transmit data, this End Device will start transmitting own data. It can avoid signal congestion caused by simultaneous data transmission of every End Device leading to the so-called "Signal Collision". The software is using C/C++ language.

4. Experiment Results and Comparisons.

4.1. Effect of different network. The comparisons among (1) Back Propagation Network (BPN), (2) RBF, (3) RBF integrated with Kohonen learning rules, and (4) other approaches are given, where two hidden layers have been adopted by BP, are as Table 3. The observation meets the expectation where the RBFN integrated with Kohonen learning rules has best performance.

4.2. Effect of neuron number. Three kinds of neuron numbers in hidden layer, analysis is tested as in Table 4.

Note Table 4 that the minimum average error takes place when there are 4 neurons in hidden layer, while Figure 16 is the errors with different numbers of neurons in hidden layer. For 4 neurons in hidden layer, the error within 90% of test sample is less than 4m. However, the error result is not decreasing with increasing neurons in hidden layer.

TABLE 3. Error comparison for different network

	Average error (m)	RMS error (m)
BP	4.87	5.07
RBF	3.96	4.48
RBF/Kohonen	3.35	3.44

TABLE 4. Comparisons for different neuron number

	Average error (m)	Root-mean-square error (m)
$n = 3$	3.35	3.44
$n = 4$	3.01	3.10
$n = 5$	4.04	4.40

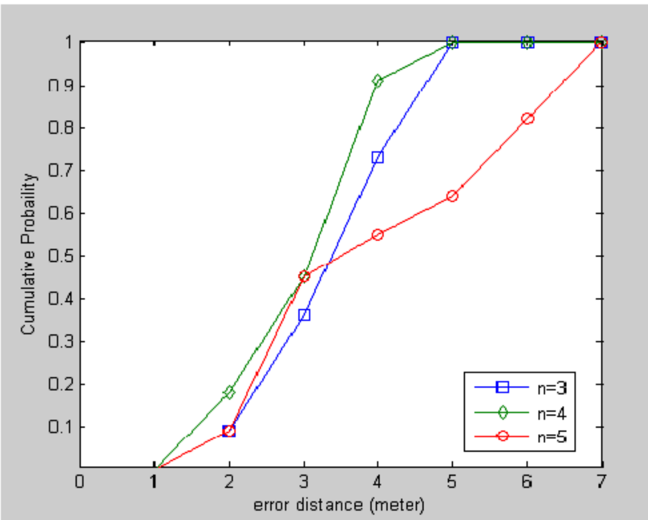


FIGURE 16. Cumulative error for different neuron number

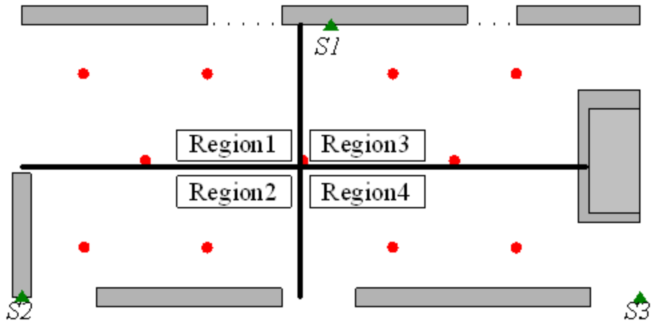


FIGURE 17. Partition environment testing

TABLE 5. Comparisons of average error for existing systems

System	Algorithm	Precision (m)%
ENRADAR (Bahl *et al.* 2000)	Nearest neighbor/environment profiling	3.16m at 90%
RADAR (Bahl/Padmanabhan, 2000)	Nearest neighbor	2.1m at 38%
Prasithsangaree *et al.* (2002)	Weighted k-nearest neighbor	7.2m at 75%, 12.2m at 95%
Youssef et al. (2003)	Bayesian	2.1m at 90%
Heaberlen et al. (2004)	Bayesian	3m at 97%
Battiti et al. (2005)	Neural network and weighted k-nearest neighbor	4.9m to 5.2m at 90%
Single-network	RBF/Kohonen	3.01m at 100%
Multi-network	RBF/Kohonen	1.47m at 90%, 2.8m at 100% 100%

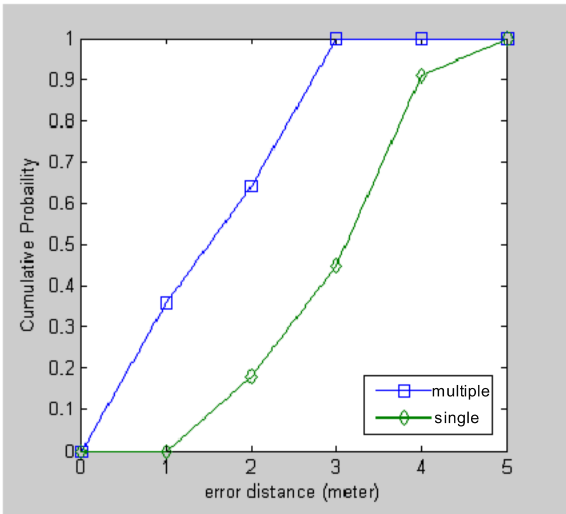


FIGURE 18. Cumulative error for single & multi-RBFN

4.3. **Effect of training area size.** As shown in Figure 17, the use of multiple RBF networks in different partitions of the same environment will affect the accuracy. There are four partitions in environment, each with one RBF network assigned for network training. The errors of testing will be compared with the error of single RBFN prior to the partition as shown in Table 5.

Table 5 indicated that the positioning by using multiple RBF networks in partitioned environment has better accuracy than the use of single RBF and other approaches. The main reason and significance of this paper is, during training process RBFN it retains memory of certain signal interference factors caused on reception of LQI in individual region such that the environmental interference factors can be reduced leading to reduced errors. The positioning precision can be attained to 3.01m 100% and 2.8m 100% for single/multi-network, respectively. Moreover, it is 1.47m at 90% in some excellent condition. However, although the use of more RBFN will enhance accuracy, the analysis of variation of LQI value received in indoor environment is still necessary for determination of most appropriate number of RBFN to be used. The use of excessive number of RBFN will occupy too much memory if it failed to enhance the positioning accuracy.

5. **Conclusion.** Integrated with Zigbee hardware, a simple yet effective intelligent indoor positioning system is proposed. The verification of IP algorithm with multi-RBFN has given better accuracy comparing with other approaches. The accuracy can be also enhanced by adjusting the number of hidden layers within certain range. It is applicable not only for robot IPS, but also more indoor information and services. It also provides various features such as greatly enhanced convenience for onsite provisioning, high feasibility, and reduced cost.

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