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Intelligent LQI-based wireless sensor network applied to ZigBee positioning system

***Abstract**. In this paper, a link quality indicator (LQI) based wireless sensor network (WSN) constructed by a recurrent fuzzy neural network (RFNN) is developed as a ZigBee Positioning System (ZPS) to monitor and realize the tag of 802.15.4/ZigBee locations. First, the performance of LQI is demonstrated, then it is applied to develop a ZPS which is used to verify the performance of indoor location identification. Finally, an RFNN is used to combine with the ZPS to develop a location system, and it can be applied for children's position monitoring. The experimental results demonstrate good positioning performance has been achieved by the proposed location system.*

***Streszczenie.** W artykule opisano sieć czujników bezprzewodowych zbudowaną za pomocą sieci neuronowej RFNN, na bazie metody LQI. Ma ona zastosowanie w protokole 802.15.4/ZigBee jako blok lokalizacji (ZigBee Positioning System). Omówione zostało zastosowanie LQI, który został wykorzystany w projektowaniu ZPS. Na koniec wykorzystano RFNN oraz ZPS w budowie systemu lokalizacji. Badania eksperymentalne potwierdziły skuteczność działania proponowanego systemu. (**Zastosowanie LQI do inteligentnej sieci czujników bezprzewodowych w aplikacji do systemu pozycjonowania ZigBee**).*

Keywords: Recurrent fuzzy neural network (RFNN); Wireless sensor network (WSN); Link quality indicator (LQI); ZigBee positioning system (ZPS).
Słowa kluczowe: sieć neuronowa, RFNN, sieć czujników bezprzewodowych, wskaźnik LQI, ZPS, ZigBee.

1. Introduction

Many applications of indoor location identification systems are based on the technologies of wireless sensor network (WSN) or IEEE 802.15.4/ZigBee standard [1]. These applications have been widely developed in many consumer products. Recently, a ZigBee Positioning System (ZPS) has been produced by *Fontal Technology Inc. Taiwan*, which also called *i-Tracer*. Many localization identification algorithms have been developed to determine the locations of sensor nodes such as the technique of estimating the Euclidean distances by using time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA) between nodes and the least-squares trilateration (LST) algorithm [2]. The technology of ZPS is based on the ZigBee physical standard via the link quality indication (LQI) which can report the signal strength associated with a received packet to higher layers of ZigBee. By using ZPS, many indoor position identification applications such as human/children care, equipment managing, emergency monitoring, security and personnel/visitor identifications, etc. have been developed [3].

The recurrent fuzzy neural network (RFNN) controller, which uses on-line learning algorithm to serve as a basis for constructing a set of fuzzy if-then rules with appropriate membership functions to generate the stipulated fuzzy output and neuron weightings, is used as an efficient learning mechanism to improve the positioning performance. The RFNN has abilities of dynamic response and the better information storing ability. Since a RFNN has an internal feedback loop, it can capture the dynamic response of a system with external feedback through delays. Thus, the RFNN is a dynamic mapping network [4, 5]. The RFNN controller can be developed in platform of *MATLAB™* software [6]. By using this RFNN, a reliable monitor can be achieved appropriately. There have already numerous applications of RFNN can be searched in academic web sources such as Google Scholar.

In this paper, the concept of LQI will be explained at first. Finally, the ZPS will be combined with the RFNN to develop a position monitoring system. In simulation, the example of children's position monitoring is illustrated to demonstrate the performance of ZPS.

2. Preliminary of ZigBee Positioning System (ZPS)

The ZigBee Positioning System (ZPS) considers only indoor environments such as inside a building where the global position system (GPS) is useless. The technology of ZPS is based on the ZigBee physical standard via the link quality indication (LQI) which reports the signal strength associated with a received packet such as the location of users or devices in personal area networks (PAN) can be determined. The mostly adopted approach of ZPS is to estimate the distance of the mobile unit from some set of measuring units by means of the signal path loss of LQI due to propagation. Theoretical and empirical models are used to translate the difference between the transmitted LQI signal strength into range estimation. The ZPS is developed by LQI algorithms [7-9]. From theoretical and empirical test for the model of LQI, if there are three location nodes, three path losses can be calculated by means of LQI methodology. All data can be stored in the servers of ZPS by using SQL language and Java language programs. The design concept diagram of ZPS is shown in Fig. 1. It is constructed by 3 servers and some tags to manage and process data such as to do some applications of position monitoring combined with RFNN monitor.

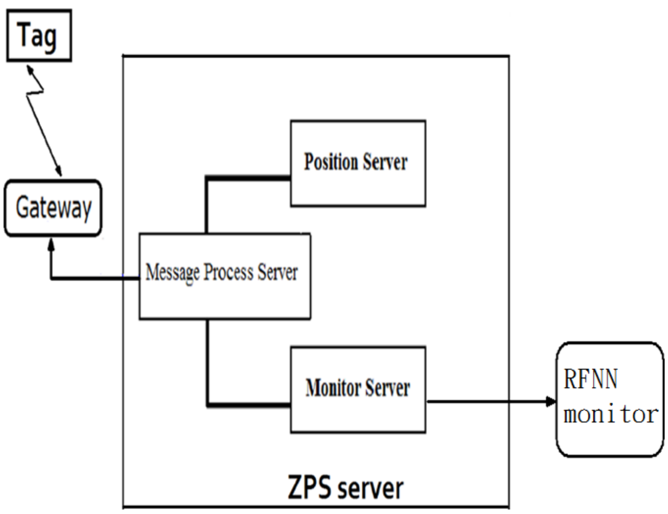

Fig. 1. Architecture diagram of ZPS

3. RFNN monitor design

Figure 2 shows a four-layer neural network [4, 5] comprising the input (the *i* layer), membership (the *j* layer), rule (the *k* layer), and output (the *o* layer) layers. This network is adopted to implement the proposed RFNN. The recurrent feedback is embedded in the network by adding feedback connections in the second layer of the fuzzy neural network. Since the recurrent neuron has an internal feedback loop, it captures the dynamic mapping network. The signal propagation and the basic function in each layer are introduced as follows:

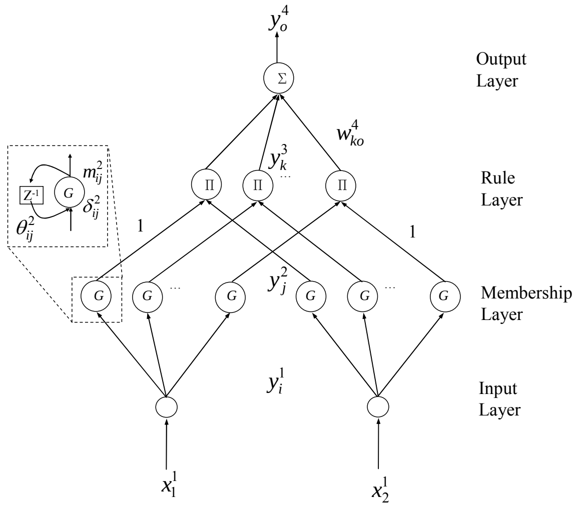

Fig. 2. Network structure of a recurrent fuzzy neural network

Layer 1 - Input layer: For every node *i* in this layer, the net input and the net output are represented as

(1) $$net_i^1(N) = x_i^1$$

(2) $$y_i^1(N) = f_i^1\left(net_i^1(N)\right) = net_i^1(N)\ ,\ i = 1,2$$

where x_i^1 represents the *i*th input to the node of layer 1 and *N* denotes the number of iterations.

Layer 2 - Membership layer: In this layer, each node performs a membership function. The Gaussian function is adopted as the membership function. For the *j*th node

(3) $$net_j^2(N) = -\frac{\left(x_i^2 + y_j^2(N-1)\boldsymbol{\theta}_{ij}^2 - m_{ij}^2\right)^2}{\left(\boldsymbol{\sigma}_{ij}^2\right)^2}$$

(4) $$y_j^2(N) = f_j^2\left(net_j^2(N)\right) = \exp\left(net_j^2(N)\right)\ \ j = 1,2,...,m$$

where m_{ij}^2 is the mean, $\boldsymbol{\sigma}_{ij}^2$ is the standard deviation and θ_{ij}^2 is the feedback gain of the Gaussian function in the *j*th term of the *i*th input linguistic variable x_i^2 to the node of layer 2, respectively, and *m* is the total number of linguistic variables with respect to the input nodes.

Layer 3 - Rule layer: Each node *k* in this layer is denoted by $\prod$, which multiplies the incoming signal and outputs the product. For the *k*th rule node

(5) $$net_k^3(N) = \prod_j w_{jk}^3 x_j^3$$

(6) $$y_k^3(N) = f_k^3\left(net_k^3(N)\right) = net_k^3(N)\ ,\ k = 1,2,...,n$$

where x_j^3 represents the *j*th input to the node of layer 3, the weights w_{jk}^3 between the membership layer and the rule layer are assumed to be unity.

Layer 4 - Output layer: The single node *o* in this layer is labeled as Σ, which computes the overall output as the summation of all incoming signals

(7) $$net_o^4(N) = \sum_k w_{ko}^4 x_k^4$$

(8) $$y_o^4(N) = f_o^4\left(net_o^4(N)\right) = net_o^4(N)\ ,\ o = 1$$

where the link weight w_{ko}^4 is the output action strength of the *o*th output associated with the *k*th rule, x_k^4 represents the *k*th input to the node of layer 4, and y_o^4 is the output of the recurrent fuzzy neural network controller.

For On-line learning algorithm, by using the sliding mode or switching control theory, the goal of control is to drive the trajectory with sliding motion that is the system trajectories will move onto a specified surface s, which is called sliding surface or switching surface. The on-line learning algorithm is a gradient descent algorithm in the space of network parameters and aims to minimize $s(t)\dot{s}(t)$. Therefore, $s(t)\dot{s}(t)$ is selected as the error function.

According to the gradient descent method, the weights in the output layer are updated by the following:

$$\begin{aligned}\dot{w}_{ko}^4 &\equiv -\eta_w \frac{\partial s(t)\dot{s}(t)}{\partial w_{ko}^4} \\ &= -\eta_w \frac{\partial s(t)\dot{s}(t)}{\partial u_{srn}} \frac{\partial u_{srn}}{\partial w_{ko}^4} \\ &= -\eta_w \frac{\partial s(t)\dot{s}(t)}{\partial u_{rn}} \frac{\partial u_{rn}}{\partial w_{ko}^4}\end{aligned}$$

(9) $$= \eta_w k_1 \frac{s(t)}{x(t)} x_k^4$$

where η_w is the learning rate with a positive constant. Since the weights in the rule layer are unity, only the approximation error term needs to be calculated and propagated by the following:

$$\delta_k^3 \equiv -\frac{\partial s(t)\dot{s}(t)}{\partial u_{srn}} \frac{\partial u_{srn}}{\partial net_o^4} \frac{\partial net_o^4}{\partial y_k^3} \frac{\partial y_k^3}{\partial net_k^3}$$

(10) $$= \frac{s(t)}{x(t)} k_1 w_{ko}^4\ .$$

The multiplication is done in the membership layer and the error term is computed as follows:

(11)

$$\delta_j^2 \equiv -\frac{\partial s(t)\dot{s}(t)}{\partial u_{srn}} \frac{\partial u_{srn}}{\partial net_o^4} \frac{\partial net_o^4}{\partial y_k^3} \frac{\partial y_k^3}{\partial net_k^3} \frac{\partial net_k^3}{\partial y_j^2} \frac{\partial y_j^2}{\partial net_j^2} = \sum_k \delta_k^3 y_k^3\ .$$

The update laws of m_{ij}^2, σ_{ij}^2 and θ_{ij}^2 can also be obtained by the gradient search algorithm, i.e.,

$$\dot{m}_{ij}^2 \equiv -\eta_m \frac{\partial s(t)\dot{s}(t)}{\partial m_{ij}^2} \equiv -\eta_m \delta_j^2 \frac{\partial net_j^2}{\partial m_{ij}^2}$$

(12) $$= -\eta_m \delta_j^2 \frac{2\left(x_i^2 + y_j^2(N-1)\theta_{ij}^2 - m_{ij}^2\right)}{\left(\sigma_{ij}^2\right)^2}$$

$$\dot{\sigma}_{ij}^2 \equiv -\eta_\sigma \frac{\partial s(t)\dot{s}(t)}{\partial \sigma_{ij}^2} \equiv -\eta_\sigma \delta_j^2 \frac{\partial net_j^2}{\partial \sigma_{ij}^2}$$

(13) $$= -\eta_\sigma \delta_j^2 \frac{2\left(x_i^2 + y_j^2(N-1)\theta_{ij}^2 - m_{ij}^2\right)^2}{\left(\sigma_{ij}^2\right)^3}$$

$$\dot{\theta}_{ij}^2 \equiv -\eta_\theta \frac{\partial s(t)\dot{s}(t)}{\partial \theta_{ij}^2} \equiv -\eta_\theta \delta_j^2 \frac{\partial net_j^2}{\partial \theta_{ij}^2}$$

(14) $$= \eta_\theta \delta_j^2 \frac{2\left(x_i^2 + y_j^2(N-1)\theta_{ij}^2 - m_{ij}^2\right) y_j^2(N-1)}{\left(\sigma_{ij}^2\right)^2}$$

where η_m, η_σ and η_θ are the learning rates with positive constants.

4. Empirical and simulation results

At first, the programs of Location nodes are developed then the program of Tag is developed consequently. Every network must have one and only one Gateway, and one of the tasks in setting up a network is to select and initialize this Gateway. The main programs of Location nodes, Gateway and Tag are developed by the application programming interface (API). The Tag identification (Tag-ID) must be set adequately in configuration program. It can provide all the software tools and hardware required to get the first-hand experience with WSN. Every board of Location nodes, Gateway and Tags are equipped with a high-power ZigBee RF module based on JN-5121 CPU (produced by *Jennic Technology Inc.*) which provides much higher covering range with 2.4GHz RF antenna [10].

For the software, *Jennic Technology Inc.* also provides free API packages to the peripheral devices on the JN5121 and JN513x single-chip IEEE 802.15.4 compliant wireless microcontrollers. This is known as the Integrated Peripherals API. It details the calls that may be made through the API in order to set up, control and respond to events generated by the peripheral blocks, such as UART, GPIO lines and Timers among others. This API does not include support for the ZigBee WSN MAC hardware built into the device; this hardware is controlled using the MAC software stack that is built into the on-chip ROM [10]. In this paper, the ZigBee WSNs are used to design for the ZPS by means of RFNN based control methodology.

At first, the LQI test is demonstrated and shown in Fig. 3. From the results, the values of LQI will be varied according to the distance between the Location nodes and Tag. In Fig. 3, the near distance test shows the high LQI but the long distance test shows the low LQI. In the programs, the real analogue to digital (A/D) values are normalized from 0 to 255. The ZPS is composed of server, Gateway, Location nodes and Tag. The experiment is proceeded by using three location nodes and one tag.

One of the experiment results diagram is shown in Fig. 4. In Fig. 4 (a), there will have three areas generated for the existences of three indoor location nodes. Because the tag is near number 1 of location nodes, the Tag number will be appeared in the corresponding location node number. By using ZPS graphic user interface (GUI), the data can be appeared in the screen and stored in SQL database. The location monitoring is one of the main experimental purposes, the data of location nodes and Tags will be transmitted to server database; meanwhile, these data will be also appeared in GUI of ZPS through Location node. For example, the Tag numbered with '9043' is near Location node 1 then the GUI will appear its Tag number in GUI such as in Fig. 4 (b). All these data will be stored in database of servers, these data can be used by SQL program and can be feed into RFNN system to construct a monitoring system.

The RFNN based controller described as aforementioned is developed. If there are three location nodes and three tags placed in three children. From the LQI data, after RFNN based ZPS controller's manipulations, the fuzzy values will be returned to the ZPS server to monitor the positions of these children. The RFNN design concept diagram is shown in Fig. 5. It is a three inputs one output system. The inference of RFNN output value is normalized from 0 to 1. For example, the long-term simulation of ten minutes is shown in Fig. 6. The children 1 with tag 1 has left his room at the time of about 3.3 minute; the RFNN will alarm the signal because it has lower than the threshold value which is set as 0.6; Also, the children 2 and 3 with tag 2 and tag 3 have left their room at about 6.8 minute; the RFNN will also alarm the signal because it has lower than the threshold value. On the other hand, when all children are in rooms the result will all has high inference values; the RFNN will not alarm any signals. In this experiment, the data of every location nodes or tags are used. This can reduce many burdens of parents for caring children. They don't need to continuously stare at their children; just only need care the alarm signal is triggered or not. In this experiment, the data of every location nodes or tags are used. The intelligent LQI-based ZPS has been induced in this paper by illustrating an example of children's position monitoring; meanwhile, the good monitoring performance is also possessed.

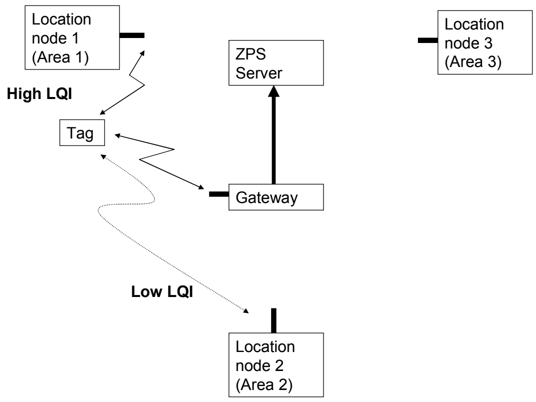

Fig. 3. Concept diagram of LQI test

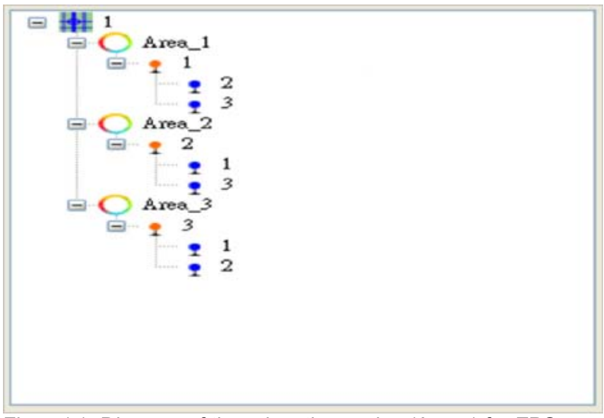

Fig. 4 (a). Diagram of three location nodes (Areas) for ZPS

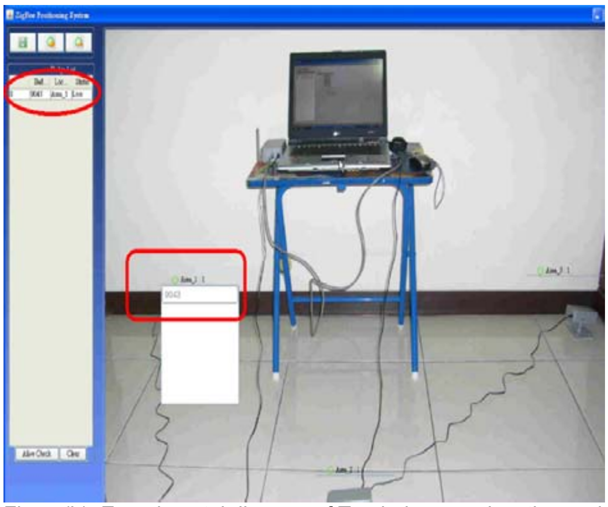

Fig. 4 (b). Experimental diagram of Tag being near location node 1

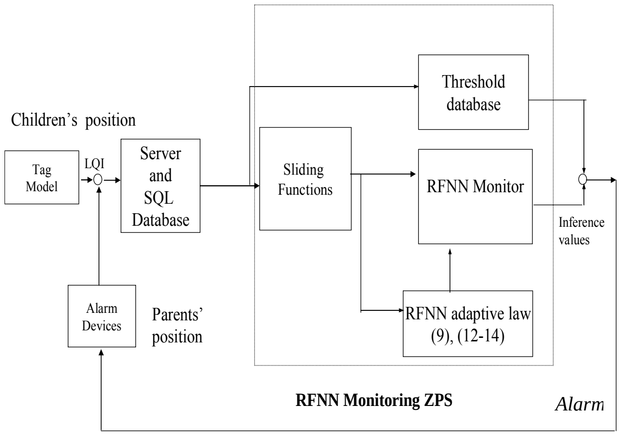

Fig. 5 The RFNN design concept diagram

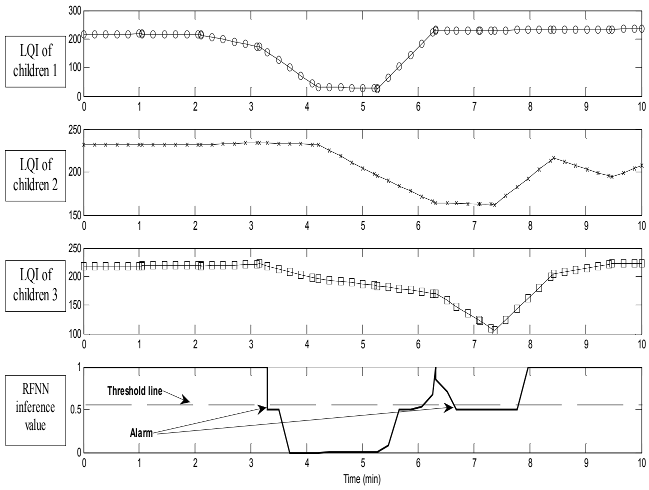

Fig. 6 The RFNN simulation results diagram

5. Conclusion

A link quality indicator (LQI) based ZigBee Positioning System (ZPS) has been established successfully. At first, the LQI is demonstrated then by using ZPS, the performance of indoor location can be verified. At last, the recurrent fuzzy neural network (RFNN) is combined with the ZPS to develop a good performance example of children's position monitoring.

Acknowledgment

This research is partially funded by the teachers' research and cooperation with company research projects of the Taoyuan Innovation Institute of Technology and supported by the SOC project of the Ministry of Education, Taiwan, R. O. C.

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