ZigBee indoor positioning system precision parameter study based on BP neural network*

Zeng Wenxiao[1,2] Wang Yanen[3] Wang Meng[1] Guo Ye[3]
[1] The Xinjiang Technical Institute of Physics & Chemistry, CAS, Urumqi, Xinjiang, 830011, China
[2]Graduate University of Chinese Academy of Sciences, Beijing 100049, China

Abstract - With the developing of wireless sensor networks (WSNs), more application approach have greatly encouraged the use of sensors for multi-target tracking. The high efficiency detection and location monitoring are crucial requirements for multi-target tracking in a WSN of indoor environment, especially the situation without the GPS application. In this paper, we proposed an indoor tracking model using Zigbee of IEEE 802.15.4 compliant radio frequency to monitor targets in a special way. Our motivation is to manipulate the erratic or unstable received signal strength indicator (RSSI) signals to deliver the stable and precise position information in the indoor environment. Based on BP neural network methodology, the selective algorithm for WSN parameters A and n values is demonstrated in this paper. An improvement Euclidian distance centroid location algorithm based on statistical uncorrelated vectors to minimize the noise in RSSI values has also been proposed here. Much more experiments about multi-target detection and location to verify the BPNN methodology can effectively improve selecting those A and n parameters in the WSN network. The system architecture, hardware and software organization, as well as the solutions for multiple-targets tracking, RSSI interference and location accuracy have been introduced in details.

Index Terms - CC2431, Zigbee location, BP Neural Network, Euclidian distance centroid algorithm, multi-target detection indoor.

1. Introduction

With the development of modern information and communication technology, wireless sensor network has become an important way to perceive the surrounding environment and monitoring environmental change. Sensor networks will be a lot of data fusion mining to get information to many users, such as temperature, humidity and alarm monitoring and other related environmental data. Especially in the field of security monitoring, personnel and equipment positioning is particularly important. Nowadays, the Bluetooth, infrared (IrDA) and wireless local area network (Wi-Fi) 802.11 are widely used in the short distance wireless communication technology. These technologies have their own characteristics, relatively speaking, although Wi-Fi coverage range is wide, but its low security is obviously. Other wireless communication technologies are high safety, but the communication distance is too short, which increases the positioning cost virtually. According to positioning mechanism, the existing location algorithms for wireless sensor networks are divided into 2 categories: Location Algorithm and range-free location algorithm. IEEE 802.15.4 [1] is a standard for wireless Personal Area Networks (PANs), which comprise devices that are characterized by low data rate, short communication range, and low cost. Depending on their capabilities, these devices can be categorized into full function devices (FFDs) and reduced function devices (RFDs). ZigBee specification [2] extends the basic star topology of an IEEE 802.15.4 PAN to a tree or mesh. In a tree topology, the root (called ZigBee Coordinator; ZC) and all internal nodes (called ZigBee Routers; ZRs) are FFDs, while RFDs can only be leaf nodes called ZigBee End Devices (ZEDs). When a ZR or ZED joins the network, it must be assigned a network address that is unique in the tree. A Zigbee network address is 16-bit long, so potentially 65,535 addresses can be assigned to all ZigBee devices in the tree (address 0 is reserved for the ZC). This amount should suffice for most applications. CC2431 is a system for wireless sensor networks Zigbee/IEEE 802.15.4 chip (SoC) solution, its hardware location engine has the characteristics of hardware requirements low, high location accuracy, can better meet the requirements of wireless location. Chen.X[3] proposed an improved methodology on the basis of Mahalanobis distance for location calculation. However, the drawback of this method is the high degree of complex learning process to obtain the RSSI value and cannot dynamically adapt to complex indoor environment. Jain.S[4] et al. illustrated backtracking algorithm on reference node space distance to improve the location accuracy. However, this improved method had been done in RSSI accept distance and weight adjustments. In fact, these traditional location algorithms suffered from the same noise influence so the environmental factors can be accommodated. Therefore, this WSN needs a lot of improvement, such as parameter the accuracy of the values selection and location algorithm of A, N, are still to be improved.

This paper focus on a new location algorithm which minimizes the noises in RSSI values first and calculates the locations based on statistical uncorrelated vectors. Much experiments show that the new calibration algorithm for A and N parameters based on BP neural network algorithm is more accurately than traditional practical methods for each location computation, which is acceptable by most users.

2. Zigbee-based indoor location system

The CC2431 is a true System-On-Chip (SOC) for wireless sensor networking Zigbee/IEEE 802.15.4 solutions. The chip includes a location detection hardware module that can be

* This work is supported by the science and technology major project of Xinjiang Uygur autonomous region (201130112).

used in so-called blind nodes to receive signals from nodes with known location's coordinate value. Based on this the location engine calculates an estimate of a blind node's position. The CC2431 enables Zigbee nodes to be built with very low total bill-of-material costs.

A. Position based RSSI technology

The path loss distribution of Received Signal Strength Indication (RSSI) conforms to the equation of path loss model, but the interference like multi-path delivery would affect the real RSSI's distribution. According to the path loss distribution of RSSI, the RSSI values are defined into four classes. The original RSSI value will be adjusted on the basis of different classes that can effectively select the p-nearest reference nodes of mobile node by Euclidean distance. Finally, the position of mobile node would be derived by calculating the coordinates of p-nearest reference nodes. Traditionally, indoor location system used the RSSI feature to estimate the distance between two objects or reference nodes. Trilateration is the regular algorithm to calculate the object's position using at least three known reference points. But the environment interference would affect the accuracy severely, like multi-path fading, temperature and humidity. The RSSI model can be described as follows "(1)". When d_0 is 1 m, and $P(d_{0,})$ can be used A*,* is calculated by using "(1)". The path loss exponent *n* is function of the environment. For some particular environments, n could be known from prior measurements. In our experimental environment, $P(d_0)$, has an approximate value of -45 and n is 3. X denotes a zero mean Gaussian random variable that reflects the interference from indoor environment.

$$P(d) = P(d_0) - 10n\lg(\frac{d}{d_0}) + X_{dBm} \qquad (1)$$

B. Parameters Definition

The radio parameter A is defined as the absolute value of the average power in dBm received at a close-in reference distance of one meter from the transmitter, assuming an omni-directional radiation pattern. The radio parameter n is defined as the path loss exponent that describes the rate at which the signal power decays with increasing distance from the transmitter. This decay is proportional to d^{-n} where d is the distance between transmitter and receiver. The actual parameter n value written to the Location Engine is an integer index value selected from a lookup table shown in Table 1[5].

TABLE I n parameter lookup table

n_index	n	n_index	n
0	1.000	16	3.375
1	1.250	17	3.500
2	1.500	18	3.625
3	1.750	19	3.750
4	1.875	20	3.875
5	2.000	21	4.000
6	2.125	22	4.125
7	2.250	23	4.250
8	2.375	24	4.375
9	2.500	25	4.500
10	2.625	26	4.625
11	2.750	27	5.000
12	2.875	28	5.500
13	3.000	29	6.000
14	3.125	30	7.000
15	3.250	31	8.000

C. Zigbee-based indoor location system architecture

Zigbee-based indoor location system includes a server, the coordinator, a number of reference nodes. It has a plurality of tracking node or the blind node, terminal based on. Blind nodes by using three edge measurement algorithm to obtain its position, the information through the reference node to the coordinator, the coordinator can act as reference nodes, is the control center of the reference node and the blind node, reference node, the blind node coordinates it will be collected to the terminal, the terminal users can obtain the blind node the positioning information, network address. The traditional Zigbee signal transmission based on the location of Fig. 2 is shown in figure.

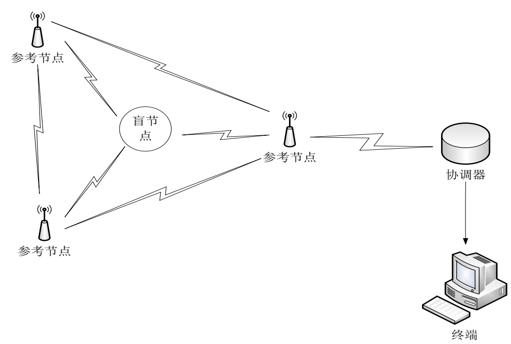

Fig. 1 Zigbee-based trilateration indoor location algorithm signal transmission schematic diagram

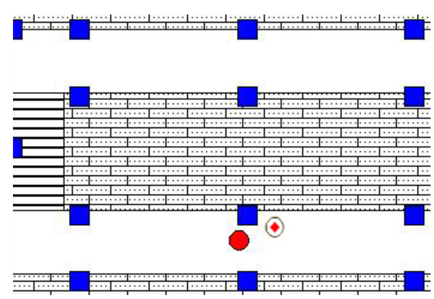

Figure.2 Indoor localation experiment monitoring interface

Figure 2 shows the upper computer software of monitoring and positioning information interface. The software architecture of Zigbee-based indoor location system mainly includes the parameter receiving module, data processing module, serial data setup module, location map display module based on. Serial data receiving module is used to receive serial data. The data processing module is used to analyze the received data, get the specific location information and network address. Location parameter settings of the parameters module is divided into two kinds of modes using a traditional method is used to set the reference node and the blind node, including the reference node placement, blind nodes involved in RSSI A, n value, environmental factors, and these parameters and the location information stored in the database, network address. Another according to the algorithm of A, the n value were optimized CC2431 engine parameters A, n are the most suitable for the working environment, in order to more rapid and accurate for the blind node location. It's working process as the map shown in figure 5. The display module is used for the location shown on the map. These modules are based on the .Net development platform and the database uses SQL Server 2005.

D. Slice pattern matching algorithm of adaptive RSSI based on Neural Network

In the algorithm, first through a large number of different indoor environment testing the environmental temperature, humidity and the obstacle wall, through the system of Euclidean distance and in accordance with the Zigbee module debugging of different A, n value. According to the K-nearest values, it will data into the system database. Combined with the neural network pattern matching algorithm, automatic access different A, n value. All A, n values make up feature values space sets P_a and all collected data sample created the data sets S, i.e.

$S=\{x : x=S_i$ （$i=1$，2，…，the total numbers of sample）} (2)

$$P_a = \{x : \rho(x, y) \le k, y \in A, x \in R^n\} \quad (3)$$

$$\begin{aligned} A = \{x : x = x_i, i = (1,2,\cdots,n), n \in N, \\ \rho(x_m, x_{m+1}) < \varepsilon, \rho(x_1, x_n) < \varepsilon, \varepsilon > 0, \\ n-1 \ge m \ge 1, m \in N\}, A \subset R^n, S \subset A \end{aligned} \quad (4)$$

In order to using actual number of neurons in the BP neural network to achieve approximate coverage of P_a, sub-regional *k*-nearest reference tags based on the geometrical correlation properties is adopted in this work. The important parameters of Zigbee network A and n values was trained in the BP neural network algorithm through aforementioned methodology. The required samples of the networks depended on complex degrees of mapping relationships. Generally, the more complicated mapping relationships, the more training samples required. A sample original sample set for S, in which the sample j a new sample set, the S'

$$\begin{aligned} S' = \{x : x = S_i', i = (1,2,\cdots,n), n \in N, \\ \rho(s_i', s_{i+1}') \le d \le \rho(s_{i-1}', s_{i+1}'), d = cons\tan t \\ (s_0' = s_j')\}, S' \subset S \end{aligned} \quad (5)$$

The jth neuron is used to approximate cover P_a and the ith neuron is covered P_i, as follows :

$$P_i = \{x : \rho(x, y) \le k, y \in B_i, x \in R^n\} \quad (6)$$

$$B_i = \{x : x = aS_i' + (1-a)S_{i+1}', a = [0, \ 1]\} \quad (7)$$

$P_a' = \bigcup_{i=0}^{j-1} P_i$ is the coverage for all j neurons in this BP neural network. Kolmogorov–Smirnov statistic quantifies a distance between the empirical distribution function of the sample and the cumulative distribution function of the reference distribution, or between the empirical distribution functions of two samples. Any continuous function can be realized by a three layers BP network, so it can be used BP neural network to nonlinear function fitting the relationship between RSSI and the distance.

E. Calibration A, N values of CC2431/2430 Zigbee-based indoor location through BP neural network

Hypothesis: n stood for neurons of an input layer, two hidden layers k_1 stood for neurons of two hidden layers, respectively, and m stood for neurons of an output layer. The best combination of the number of hidden layers, hidden neurons, choice of input factors, training algorithm parameters, etc., can be identified by these methods even though they are mostly case-oriented. According to the corresponding relationship between RSSI and d, this algorithm determines the input and output layers of BP neural network. However, hidden layer number, the number of neurons in each layer and the incentive function and training function selection is too difficult. First, using Zigbee wireless location system has a large amount of data and the corresponding distance RSSI in the practical application environment. In the analysis of simulation results, fixed in each hidden layer nodes, this paper is fixed at 16 neurons, observation of the hidden layer number from the fitting effect to one layer, two layers, three layers gradually changes. Finally, one layer simple network structure has been adopted in this work as shorten training time and easily implement. According to the fitting result, BP neural network model used the network structure of final 1 : 16 : 1.

3. Experimental results and analysis

A. Experiments description

The experiment was divided into 840 groups in this Zigbee-based indoor location system. The first 420 groups experiment's parameters calculated by the normal l experience and the left 420 groups' A and n values should be automatically determined by the neural network algorithm.

The experiment is done in a 60m (length) × 4.25m (weight) building corridor with one stairs shown as figure 2. Using 16 node rectangular topology have been done in these experiments, and the two adjacent receiver reference node distances had been increased from 5m, 10m, 15m, 20 m, 25m, 30m independent incremental measurement. The positioning distance average error and variance were calculated in this work on the basis of CC3431/2430 chip engine.

B. the parameter A and n were calculated on the basis of the BP neural network

Fig 3 and 4 shows that BP neural network can improve the present only empirically selected status of A, n value on the basis of CC 2431/2430 Zigbee location engine chip in these experiments. Through a lot of experiments comparing Figure 3 and Figure 4 can be explicitly A, n value by the neural network algorithm closed to the trial and error method to provide A, n values. This process verified that the BPNN method is effective for this Zigbee-based indoor location system. Due to changes in environmental factors, CC2431 A, n WSN sensor networks in Zigbee will also change accordingly.

Figure 3, 4 also show that, the BPNN method and the traditional method based on the A, n value tendency basic consistent. And it also showed that the method is effective and reliable. At the same time, in order to improve that the proposed parameter selection method, this paper accomplished 840 groups of experiments. The experimental results showed that the data selection method is very effective and reliable.

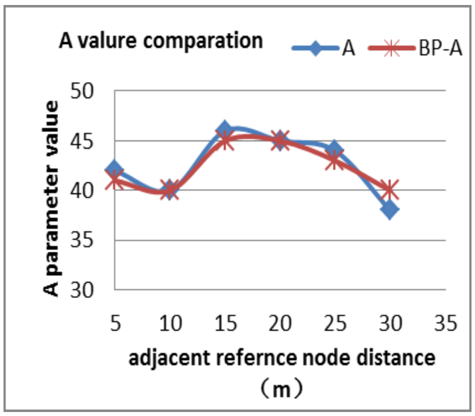

Figure 3

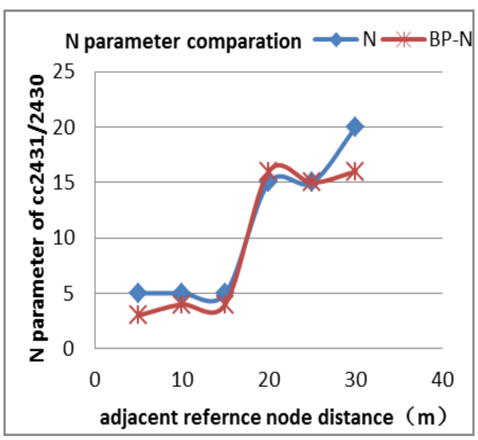

Figure 4.

4. Conclusion

Compared other location experiments, Zigbee-based indoor location system has much characteristics such as high precision, reliable transmission distance, wide coverage, low cost. In this paper, the BP neural network method has been automatically selected the location engine optimal parameters A, n value. This Zigbee-based indoor location effectiveness of this method is validated by much more experiments. The A and n values by BP neural network calculation in the Zigbee-based indoor location approach can alleviate the influence of dynamic indoor environment that can effectively calculate the mobile node's location in real time. This approach not only improves the accuracy, but also provides less calculation complexity than other improvement methods.

In this paper, Zigbee-based wireless sensor network for indoor positioning structures has a certain reference value. Users can arrange the reference nodes or receiver router's topological coordination position indoor space according to the analysis of this article in the arrangement of reference nodes and selection A, n value when setting the parameters. So it can improve the accuracy of wireless network, reduce the error, to realize low cost, high precision location. Comparing the results with that of traditional methods, the proposed methodology reduces about 0.25 to 0.75m estimation error distance and has 30% improvement on average error distance.

Acknowledgment

The work was supported by the science and technology major project of Xinjiang Uygur autonomous region (201130112)

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