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Indoor Positioning System Based on BP Neural Network Optimized by Genetic Algorithm Using ZigBee Wireless Sensor Network

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Abstract: Accurate and efficient indoor positioning is increasingly essential for a wide range of applications. Traditional indoor positioning systems, such as those using RFID, ZigBee, or ultra-wideband technology, have been hindered by multipath propagation, signal reflection, and interference in complex environments. This paper proposes an indoor positioning system utilizing a BP (Back Propagation) neural network optimized by a genetic algorithm, based on the ZigBee wireless sensor network. The method addresses inaccuracies in received signal strength indicator (RSSI)-based non-ranging algorithms, improving signal acquisition and filtering for higher precision. Experimental results demonstrate that the proposed system achieves an average positioning error of just 0.22 meters for non-training points within a 2m × 2m range, marking a significant improvement in indoor positioning accuracy.

Keywords: Genetic Algorithm; BP Neural Network; Zigbee; Indoor Positioning; Wireless Sensor Network.

1. Introduction

The need to quickly and accurately access the terminal location information and location services is growing increasingly urgent in both indoor and outdoor environments. At present, the technologies used in the indoor positioning system include RFID, ZigBee, ultrasound, video, ultra-wide band, etc. The positioning algorithm is divided into ranging and non-ranging based to whether the distance is determined. The former mainly includes TOA (Time of Arrive), AOA (Angle of Arrive), TDOA (Time Difference of Arrive) and other methods, while the latter mainly includes the positioning algorithm based on the received signal intensity RSSI (Received Signal Strength Indicator). These factors will greatly reduce the accuracy of the distance estimation due to the multi-path propagation of the indoor wireless signal and the imprecision of the reference clock. In addition, the indoor distance between equipment is short, there are serious reflection, diffraction and diffraction non-line propagation, signal in the multiple component time is quite close, the resolution of the existing equipment is not enough to distinguish the time so close to each signal, so accurate TOA estimate or TDOA estimate, almost impossible [1]. RSSI-based technology has the advantages of low hardware cost of detection equipment, stable and reliable measurement signal, and simple positioning algorithm. Therefore, the positioning technology based on RSSI non-ranging has become a hot topic for indoor positioning research [2] in recent years.

At present, the low-cost ZigBee wireless ad hoc network technology is developing rapidly, which can provide the receiving signal strength RSSI, link quality LQ (Link-Quality), transmission power level TPL (Transmit Power Level) [3] and other parameters, so the ZigBee system can easily use the non-ranging based positioning algorithm. The RSSI-based non-ranging positioning algorithm is still disturbed during the signal acquisition in the positioning stage, so it is necessary to filter the collected

RSSI information, and then use the matching positioning algorithm to improve the accuracy of positioning.

In the matching localization algorithm, although the BP neural network can effectively control the average localization error, it also has the disadvantage of relying too much on experience for the choice of local optimality and structure and type. In the positioning technology proposed in this paper, the BP neural network (hereinafter referred to as GA-BP neural network) method based on genetic algorithm is used for positioning, which can effectively control the average positioning error and avoid falling into the local optimum. It is a high-precision indoor positioning technology with low computational resource consumption and low cost.

2. Positioning Principle

2.1 RSSI

The system adopts modular design to realize the following functions:

The received signal intensity (RSS) is the quantification of the energy of the received signal. Clearly, the RSS values will vary with the distance between the devices. According to the Friis free-space transfer formula [4-7], The received energy decreases as the distance between the sending and receiving devices decreases.

2.2 Finger-printing

RSSI values decrease with increasing distance, and this change is not regular because of various disturbances. Fingerprinting is divided into two stages. Fingerprinting This irregular change of the RSSI, that is, the additional interference change, is stored in the database during the pre-processing stage. In the positioning phase, use the RSSI in the database, and the RSSI value of the current alignment and locate. The RSSI in the database has features that change according to the environment, which reduces the robustness of the Fingerprinting method, but increases the accuracy of the Fingerprinting in the current environment.

3. Conceptual Design

The two main control chips used in the hardware design of the device are STM32F103VET6, and its core is Cortex-M3.ZigBee Can work in three modes: coordinator, router, and terminal mode. The coordinator is responsible for establishing the network and controlling the network access of other nodes. After establishing the network, the function of the coordinator is the same as the router, and it is responsible for the transfer of data. Unlike the router, the terminal can only communicate with the parent node, and cannot communicate directly with other nodes.

In the positioning system, the node with known location is the anchor node, the node with unknown location is the mobile node, and the node connected to the computer to transmit data is the gateway, as shown in Figure 1. Because the use of star topology networking has the characteristics of simple structure, and meets the requirements of the positioning system proposed in this paper. So the topology of the positioning system uses a star-shaped structure. The anchor node only communicates with the mobile node, so the anchor node uses the terminal.

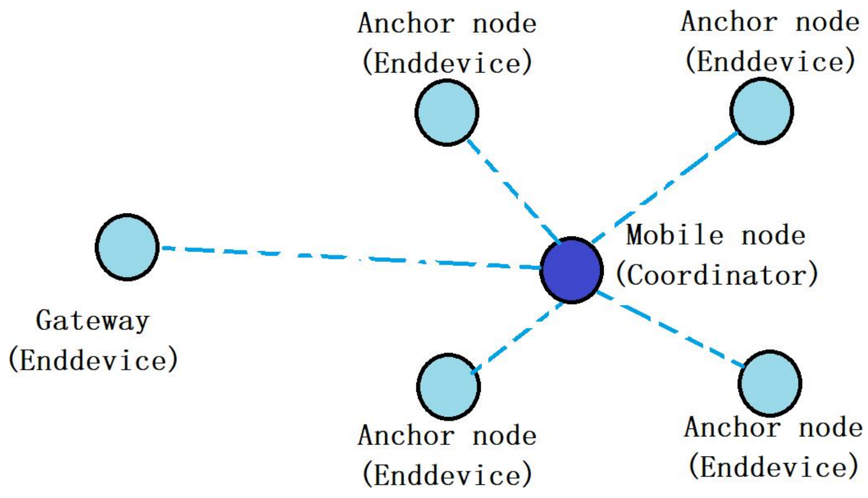

Fig 1. Network topology of positioning system

Using the star network as shown in Figure 1, the mobile node collects the RSSI values sent by the four anchor nodes and then transmits them to the computer, which calculates the coordinates of the moving nodes. The RSSI values were collected as follows:

Step1: Each anchor node sends the device ID number (number 1~4) to the mobile node at 200 m s intervals;

Step2: The mobile node receives the ID number sent by the four anchor nodes and reads the RSSI value from the receiving packet;

Step3: Move the node collects the ID number sent by the four anchor nodes, and sends the ID number and the corresponding RSSI value to the gateway;

Step4: The gateway sends the data to the computer through a serial port.

The positioning data processing part is divided into two stages: pre-processing stage and positioning stage.

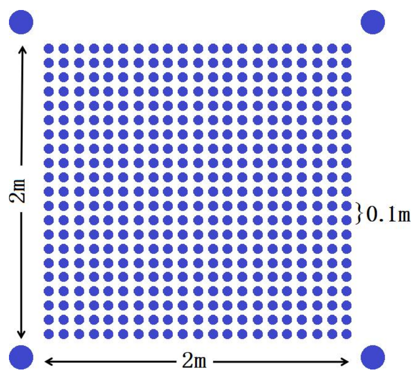

Fig 2. Experimental area

As shown in Figure 2, the large circles in the four corners represent the anchor nodes, and each small circle in the middle represents a pre-processing point. The experimental area was 2m×2m squares with a pre-processing point every 10 cm. In the pre-processing phase, the moving node is placed at the pre-processing point to collect the RSSI, data, and is collected 200 times per point, and then the average RSSI is calculated, and then the average is deposited in the database. The RSSI means and coordinates correspond one-to-one, as shown in Table 1.

After measuring the RSSI of all 361 points, and the average value, the average RSSI value was taken as the input to the BP neural network, and the coordinates corresponding to the average RSSI value were used as the output for BP neural network training.

Table 1. RSSI values corresponding to coordinates

$\overline{R_1}, \overline{R_2}, \overline{R_3}, \overline{R_4}$	x, y
.0(49.64,5135,53.71,23.3)	(0.1,1.9)
(45.101,47.99,49.14,2556).0	(0.2,1.9)
(48.77,51.223,5234,27.68).0	(0.3,1.9)
…	…

The BP neural network is a supervised learning artificial neural network. The learning process is composed of the forward propagation of the signal and the reverse correction of the error. A typical three-layer BP neural network includes an input layer, a hidden layer, and an output layer. The Kosmogorov's theorem states that a three-layer BP neural network can fit any continuous nonlinear curves. However, because the correspondence between RSSI values and coordinates is not continuous, a four-layer BP neural network, which contains two hidden layers, is required.4 RSSI need to be measured in the positioning system, so the input nodes of the BP network are 4. You want to obtain the corresponding coordinates (x, y) through 4 RSSI values, so the output nodes are 2. There is no fixed specification when designing the number of nodes of the hidden layer. According to the experience, the number of nodes in the hidden layer 1 is 10, and that of the hidden layer 2 is 6.

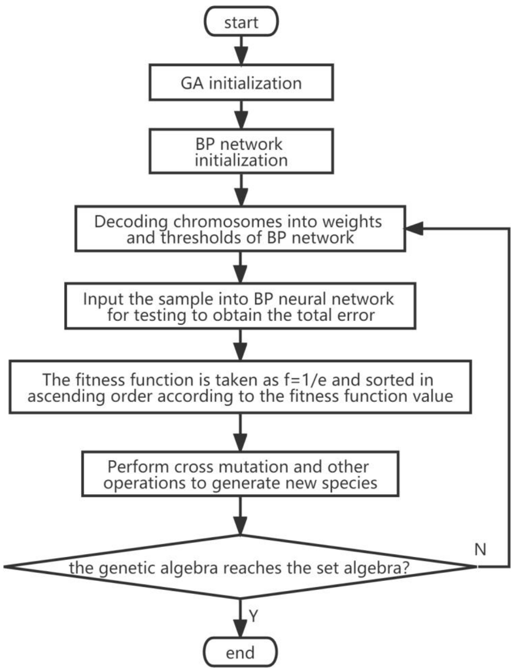

Fig 3. Flow chart of GA-BP network training

Using only the BP neural network for training is easy to fall into the local optimal.

The global optimum cannot be reached. Combining the BP neural network and the genetic algorithm can solve the above problems. In the learning process of BP network, gradient down algorithm is no longer used, but genetic algorithm is used for learning. The training process of the GABP network is shown in Figure 3. GA encoding using the real code, if the binary bit string is used, the length of the chromosome will be too long Benefit to calculate. Arrange the weight of the four-layer BP network:

W1,W2&W3, threshold:*B1,B2&B3 as a* sequence of chromosome, and these six parameters represent one BP neural network, each value in the chromosome has an upper and a lower limit, in turn as constraints, whose initial values can be generated by random numbers.

Training with BP artificial neural network, the most important thing is the generalization ability of the artificial neural network, so the samples need to be divided into two groups, one group is used as training, the other group is used as a test. Theoretically, the training error will decrease all the time, but the generalization ability will be weaker as the training error is reduced. The test error is shown in Figure 4.

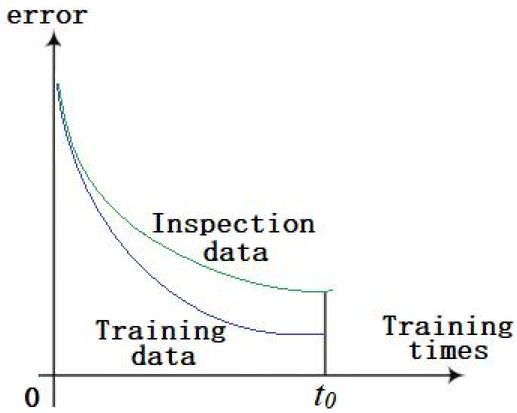

Fig 4. Relationship between error and training frequency of BP neural network

As can be seen from Figure 4, the network error shows a trend of decreasing first and then increasing, that is, over training occurs. You can see that there is an optimal training session number of times t_0, If stopping training will occur before the optimal training number is reached Insufficient training, after reaching the best number of training, but also training, test error increases, there will be excessive training. So the key to BP neural network training is to find the best number of training times. To determine whether the above two problems occur in the training, the error function is defined as:

$$error_i \quad \sqrt{(x_{oi}-x_{di})^2+(y_{oi}-y_{di})^2}$$

In formula: (x_{0i}, y_{0i}) Is the output coordinate value of the BP network of the *i*-th pre-processing point; (x_{di}, y_{di}) Is the actual coordinate value of the *i*-th pre-processing point. Divide the sample into $\overline{error}$ In two groups, *n* (*n* = 0,1,2,..., 361) is the sample number, and the sample of (*n*%11 == 0) is formed into the training group, (*n*%11 != 0) The sample consists of the test group. The training group data is used to train the BP neural network, and the test group data is used to determine whether the training should be stopped. When using a genetic algorithm, we need to choose the appropriate fitness function and determine the excellent individuals in the parent according to the values of the fitness function. Each individual in the population is decoded into the weight and threshold of the BP network, and the training group data and the test group data are sent to the BP neural network for training. According to Equation (3), the error of each point in the training group and the error of each point in the test group are obtained, and then the errors of the two groups are averaged as $\overline{error}$. The fitness function is selected as the reciprocal of the average error of the training group, and the test group average error is used to determine whether the global optimal is reached, that is, whether the best training times t_0 is reached。

4. Experimental Measurement

The GA-BP neural network training results are shown in Table 2.

Table 2. Training results of GA-BP neural network

BP neural network	training $\overline{error}$	checkout $\overline{error}$
1	0.21	0.22
2	0.187	0.221
3	0.193	0.206

As can be seen from Table 2, BP1 was under-trained compared with BP3, and BP2 was over-trained compared with BP3, so BP3 was selected for indoor localization.

The positioning experiment was carried out on the experimental area used in the pre-processing stage. When the mobile node was placed in the experimental area of 2m×2m, the actual position of the mobile node and the observed value of the position of the positioning system were measured respectively, and the positioning error was obtained as shown in Table 3.

Table 3. Positioning error of mobile node

Actual location of the moving node at/m	Observations/m of the positioning system	Positional error
(0.3,0.82)	(0.256,0.72)	0.109
(0.5,0.82)	(0.41,0.74)	0.120
(0.7,0.82)	(0.53,0.95)	0.214
(0.9,1)	(0.70,0.78)	0.297
(1.1,1.1)	(0.94,1.17)	0.174
(1.3,1.2)	(1.14,1.49)	0.331
(1.5,1.2)	(1.43,1.52)	0.327
(1.7,1.2)	(1.57,1.37)	0.214
(1.9,1.4)	(1.75,1.33)	0.165

5. Conclusion

On the basis of ZigBee wireless sensor network, this paper proposes an indoor positioning system based on BP neural network optimized by genetic algorithm. The experimental results prove that this method can be used for accurate positioning indoors, with the average positioning error of 0.22 m for the non-training points in the positioning range of 2m×2m.

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