Research on Indoor Location Technology based on Back Propagation Neural Network and Taylor Series

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Abstract: The traditional indoor location algorithm based on distance-loss model mostly turn received signal strength indicator RSSI into distance, and then through the location-distance algorithm to achieve positioning. These algorithms need fit the wireless signal propagation model parameters A and N through experience or large amounts of data, so they are dependent on experience and are not strong universal algorithms for location of the different environment, also low accuracy. After lots of research and analysis of radio signal propagation model and the traditional indoor location algorithm, a new indoor location algorithm uses BP neural network to fit the distance-loss model is proposed. From a number of distances between reference nodes and blind node, Taylor series expansion algorithm is used to determine the coordinates of the blind node. Finally, the experiment result shows that the new algorithm improves the positioning accuracy and universality, compared with the traditional positioning algorithms.

Key Words: Indoor location, Back propagation neural network (BPNN), Received signal strength indicator (RSSI), Zigbee, Taylor Series.

1 Introduction

The Internet of Things is known as the third wave of the world's information industry development after the computer and the Internet. The ultimate goal of The Internet of Things is to provide location-based services LBS. So the location recognition as core and key technology of The Internet of Things is attracting more and more attention of the public.

People have been researching on position recognition for Open outdoor space for a long time. And many technologies on this aspect such as GPS navigation and mobile cellular networks positioning technology have been put into use and bring us great convenience. But research on position recognition for people in indoor space such as in buildings, underground parking, coal mine etc. is not as sufficient as research on position recognition for outdoor spaces, especially in our country[1]. Today there are not a very mature product and corresponding research results on the market. Because of all these reasons, we are spurred to spend more attention, time and money on indoor location research.

According to the current indoor location study, the indoor positioning technology can be divided into the following categories according to different means by which the indoor location algorithm used[2]: algorithm use radio signals, algorithm use infrared, algorithm use ultrasound, algorithm use laser, algorithm use image or video and so on. The accuracy of algorithm use infrared, laser, ultrasonic, video and image is relatively higher, but require a visual environment that nothing blocks the path. Algorithm use ultra wideband UWB, Bluetooth require additional equipment result in high cost, and the positioning range is also very small. Considering all these factors, location algorithm use Zigbee technology based on the received signal strength RSSI is chosen.

Traditional indoor positioning technology based on RSSI basically use the wireless signal propagation model, in different environments, firstly fit the unknown parameters A and N in wireless signal propagation model, or set A and N by experience, then according to some location distance algorithm to eventually achieve location[3][4]. However, this method is too dependent on experience, and also can not be used to different environments, the accuracy is not high enough. In the study and analysis of wireless signal propagation model and the traditional indoor location algorithm, a better indoor location algorithm based on BP neural network and the Taylor series expansion is proposed. The input value of the BP neural network model is RSSI, and the output value is distance, and then the Taylor series expansion algorithm is used to determine the coordinates of the blind node. Compared with the traditional positioning algorithms, the algorithm we used reduces the positioning error, avoid fitting the unknown parameters A and N in wireless signal propagation model, and in the end improve the positioning accuracy.

2 Indoor Location Technology

2.1 Relationship between RSSI and d

The radio signal strength is gradually weakened with the propagation distance increases, and there is a certain relationship between the RSSI and distance d. The reality is that the radio wave propagation mechanism is not unique, it is subject to reflection, scattering and diffraction, etc., especially in the interior, and the signal spread conditions are much more complicated[5]. The following chart shows the relationship between the RSSI and distance:

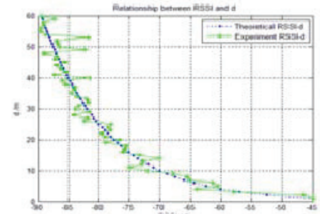

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Fig.1 Relationship between RSSI and d

Location algorithm will now consider the general impact of the barrier indoors, at present; the model-Shadowing[6] is widely used in indoor location as follow:

$$p = p_0 + 10n\lg(\frac{d}{d_0}) + \zeta \qquad (1)$$

In formula (1) d_0 is the reference distance, p_0 is the received signal strength when the distance is d_0, d is the true distance, ζ is the shadowing factor, in practice, we often use the simplified Shadowing model:

$$P = P_0 + 10n\log_{10}\left(\frac{d}{d_0}\right) \qquad (2)$$

Usually take d_0 = 1m, resulting in the practical application of the RSSI ranging formula, such as formula:

$$RSSI = -(10n\log_{10} d + A) \qquad (3)$$

A and n is the unknown parameter in formula (3), where A is the average absolute received signal strength 1m from the source of signal, and n is a signal transmission constant, it is environment-related, in other words, it is different in different environment[7].

To sum up, whether it is an ideal environment or indoor environments, it is certain that there is a relationship between RSSI and distance. The Kolmogorov theorem proves that an arbitrary continuous function can be fitted by a three-layer BP network, so we can use the BP neural network to fit the non-linear function between received signal strength RSSI and the distance d[8][9].

2.2 BP Neural Network Model for Fitting the Wireless Signal Propagation

Firstly we use CC2431 positioning system to get a great deal of RSSI and d data between reference node and blind node in practical application environment, determine the number of layers and the network nodes of each layer, transfer function and training algorithms of the BPNN. Use the measured RSSI and d to train the BP neural network, and use actual data to verify the training results, if trained successfully, save the neural network. in the positioning process, enter any of the RSSI value into the well-trained BP can we get output as the corresponding distance d value, then with any three or more of the distance d and the coordinates of the known reference nodes, we can use Taylor series method to determine the location coordinates of the blind node to achieve positioning. Shown as figure 6 below:

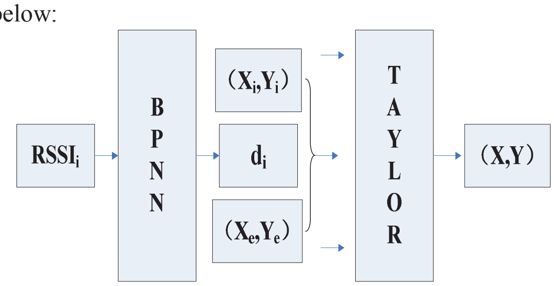


Fig.2 Flow chart of the location system

And according to the relationship between RSSI and d, to determine the neuron number of input and output layers of BP neural network is both one neuron. However, it is difficult to determine the neuron number of each hidden layer and the hidden layer numbers select the right activation functions and training functions in the design of BP network, there is no theoretical guidance. After lots of trial, the BP neural network with a 1:26:1 architecture is much better, the training time is short, the best fitting results, we can achieve the desired results.

The basic BP algorithm has unsatisfactory anti-interference ability, slow convergence and easy to fall into local extreme points[10]. Matlab neural network toolbox provide us a dozen fast learning algorithms, over repeated experiments and comparative studies we last chose traincgf algorithm. The algorithm does not increase the algorithm complexity, improve the convergence speed, and can reach the global minimum, BP neural network training and validation results shown as below:

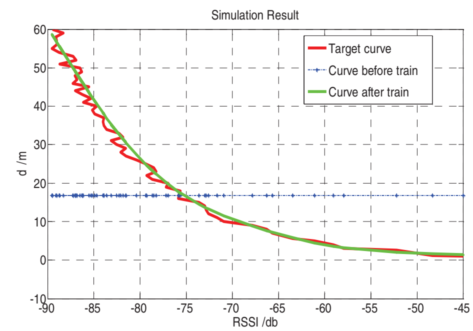


Fig.3 Map of BP train and simulation

2.3 Taylor Series Expansion Method to Estimate the Position

When get at least three distances between reference nodes (x_i, y_i) and the blind node through the well-trained BP neural network, then set a blind node coordinates as the initial value on experience, then we can get an equation about the measured distance and the estimated distance as follows:

$$f_i(x_e, y_e) = |d_i - \sqrt{(x_i - x_e)^2 + (y_i - y_e)^2}| \qquad (4)$$

Conduct Taylor series expansion to the above equation and retain only the first-order partial derivative, neglect the subsequent item, we get the following Formula (5):

$$\begin{aligned} f_i(x,y) &= f_i(x_e + \Delta x, y_e + \Delta y) \\ &\approx f_i(x_e, y_e) + \frac{\partial F_i}{\partial x_e}\Delta x + \frac{\partial F_i}{\partial y_e}\Delta y \end{aligned} \qquad (5)$$

Formula (5) can be written in matrix form: $f = A\Delta$, solve the matrix equation can we get: $\Delta = (A^T A)^{-1} A^T f$, in which:

$$\Delta = \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}$$

$$A=\begin{pmatrix}\frac{\partial F_1}{\partial x_e} & \frac{\partial F_1}{\partial y_e}\\ \vdots & \vdots \\ \frac{\partial F_i}{\partial x_e} & \frac{\partial F_i}{\partial y_e}\end{pmatrix}$$

$$=\begin{pmatrix}\frac{(x_1-x_e)}{\sqrt{(x_1-x_e)^2+(y_1-y_e)^2}} & \frac{(y_1-y_e)}{\sqrt{(x_1-x_e)^2+(y_1-y_e)^2}}\\ \vdots & \vdots \\ \frac{(x_i-x_e)}{\sqrt{(x_i-x_e)^2+(y_i-y_e)^2}} & \frac{(y_i-y_e)}{\sqrt{(x_i-x_e)^2+(y_i-y_e)^2}}\end{pmatrix}$$

$$f=-\begin{pmatrix} d_1-\left[(x_1-x_e)^2+(y_1-y_e)^2\right]^{1/2} \\ \vdots \\ d_1-\left[(x_i-x_e)^2+(y_i-y_e)^2\right]^{1/2}\end{pmatrix}$$

After get $\Delta=\begin{bmatrix}\Delta x\\ \Delta y\end{bmatrix}$, we make some modify as follows: $x_e{}'=x_e+\Delta x$, $y_e{}'=y_e+\Delta y$, repeat the process until Δx, Δy is small enough to meet pre-set threshold ε, as $\Delta x+\Delta y\le\varepsilon$, at this time (x_e, y_e) is the estimated location of blind node.

3 Indoor Positioning System Design

3.1 Composition of The Indoor Location System

Positioning System has four main components: the gateway, reference node, blind node (also called positioning node or mobile node), and monitoring software. the core of the Gateway is CC2430 or CC2431, it is like the brain and heart of the whole positioning system, is responsible for the formation of a location network, assign address for new nodes join the network, remove nodes out of network, and interactively communicate with the upper machine, maintain networking and communication operation between each node. Reference node is made up of CC2430 or CC2431, a kind of static node with artificial known coordinate, the node responsible for transmitting the signal from blind node to RSSI and passing it back to the blind node, transfer information between different nodes as a transfer station, the reference node does not participate in position calculation. The blind node is composed by the CC2431, location to be determined, mobile node. The blind node should be within the network formed by the reference node. According to the received signal strength RSSI and coordinates sent back by reference nodes, to achieve positioning. Monitoring part is the monitoring software on PC, communicate with the gateway through the PC serial port, display positioning information, communicating information between nodes in real-time on the screen send up by the gateway, in addition pass down some man-made parameters through the gateway, and send to each node. The location platform is shown in Figure 4:

Fig.4 Map of the positioning system

3.2 Positioning process

Lay reference nodes in the locating environment and set their coordinates in advance, then open the gateway to establish a network, after that open the reference nodes and blind nodes. Positioning algorithm is completed in blind node, the reference nodes does not participate in the positioning algorithm, the positioning system operation flow chart is as follows:

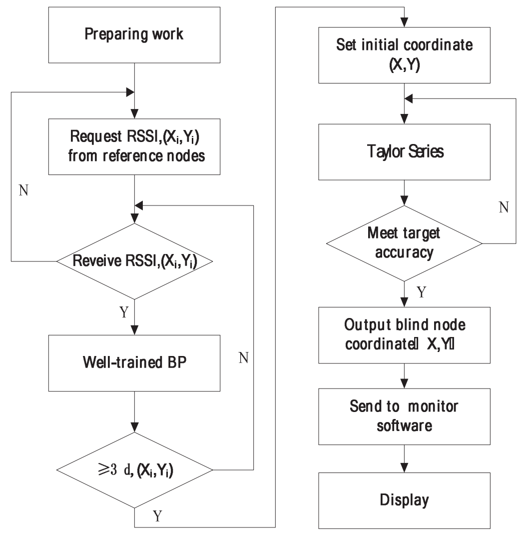


Fig.5 Flow chart of the positioning algorithm.

4 Experimental Verification of the Location Algorithm

4.1 Construct the Environment Scene

We take the underground parking lots beneath The Humanities Building in our school as the experimental environment shown in Figure 6. The experimental area is a rectangle with size of 48.2X26.0m, the experimental area plan is shown as in Figure 7. We place reference nodes around the experimental area with a distance of 8m from each other, totally 18 reference nodes are placed, and set coordinates for these reference nodes. During the experiment, the blind node carried by people is moved from one place to another within the region surrounded by the reference nodes, the blind provides one position signal every five seconds, and the coordinates are displayed on host computer. Record and save the blind node's actual position coordinates and calculated coordinates.

Fig.6 Map of the experimental scene

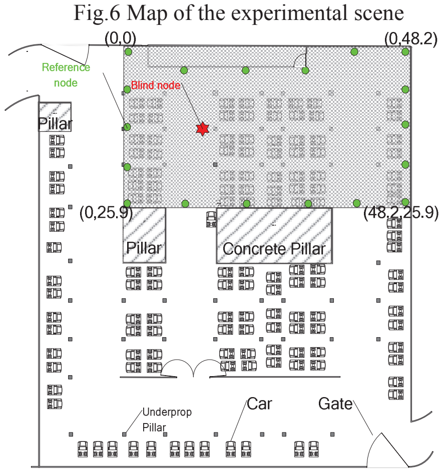
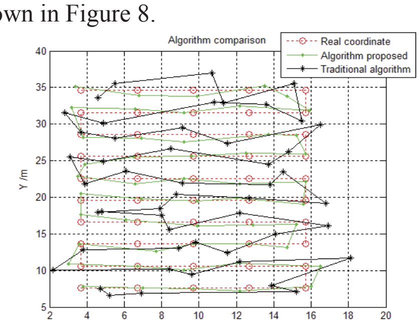


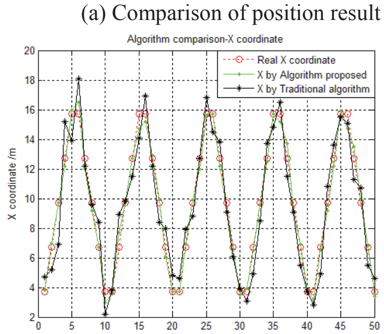
Fig.7 Ichnography of the experimental scene

4.2 Experimental Results

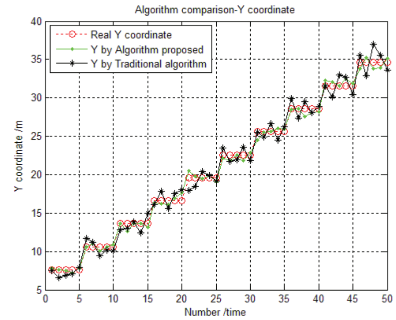
The experimental result is shown in chart 8. After analyzing the experimental data, compare the performance of traditional indoor location algorithm and the position location algorithm proposed in this article, Comparison is shown in Figure 8.



(a) Comparison of position result



(b) Comparison of X coordinates



(c) Comparison of Y coordinates

Fig.8 Comparison of different algorithm

As can be seen from Figure 8, the position location algorithm proposed in this article control positioning error within 2m, compared to the traditional 3 ~ 5m of the positioning error, the proposed algorithm improves positioning accuracy.

5 Conclusions

First, introduce the common indoor location algorithm and its advantages and disadvantages; describe the principle of the traditional indoor location algorithm based on the wireless signal propagation. Then focus on the proposed algorithm based on BP neural network and Taylor series expansion method for position estimation with positioning platform CC2431. Compare the performance of common RSSI location algorithm and the location algorithm article proposed through matlab simulation and practical experiments. From the experimental results can be seen, the proposed algorithm reduces the positioning error and improve the positioning accuracy, proved the superiority of the algorithm.

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