

Indoor Positioning Optimization Based on Genetic Algorithm and RBF Neural Network

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Abstract—In UWB wireless indoor positioning, due to the influence of the indoor environment, the ranging error is often very large. In order to eliminate the influence of these environmental factors as much as possible and improve the accuracy of indoor wireless location, an indoor positioning optimization algorithm combining genetic algorithm and RBF neural network(GA-RBF) is proposed in this paper. We use genetic algorithm to find the optimal parameters of RBF network, so as to give full play to the advantages of RBF neural network for fast and high precision approximation. A large number of sample data are used to train genetic RBF neural network, the experimental results show that the positioning error of this algorithm is within 10cm, which can achieve a high positioning accuracy in the not line of sight (NLOS) environment. Compared with the traditional RBF neural network algorithm, its optimization performance has been greatly improved.

Keywords—UWB, indoor positioning, RBF neural network, genetic algorithm

I. INTRODUCTION

In recent years, the industry related positioning technology and services are rapidly moved from outdoor to indoor, and many wireless positioning technologies have made great progress. As a new wireless location technology, UWB has the characteristics of strong anti-interference ability and good penetration. Compared with other wireless positioning methods, it has better positioning accuracy in the actual indoor positioning, and has becoming a hot research topic in the indoor wireless positioning area. However, in the indoor environment, due to the influence of various obstacles, the positioning accuracy cannot meet the requirements in many cases, so it is necessary to reduce or eliminate the influence of such errors. Paper [1] proposed an radio frequency identification devices(RFID) indoor positioning algorithm based on particle swarm optimization artificial neural network(PSO-ANN). By optimizing the weight and threshold of the neural network, an accurate classification model was established to learn the relationship between the received signal strength indication(RSSI) and the label position. Paper [2] use back-propagation(BP) neural network to improve the indoor positioning accuracy, which verified that BP method is superior to other existing popular positioning algorithms, and can be regarded as an alternative program. In paper [3], part of the large data set is used to train artificial neural network (ANN) and applied to error prediction. It is proved that this method can greatly improve the ranging performance of UWB and the accuracy of

positioning system.

Radial basis function(RBF) networks is an artificial neural network which uses radial basis function as activations. It has the ability to approach any continuous function with any precision, its structure is simple, its training method is very convenient, and its learning convergence speed is very fast. All these characteristics are very suitable for time series analysis, pattern recognition and nonlinear control [4-5]. Aiming at optimizing indoor UWB positioning accuracy, this paper attempts to apply genetic algorithm to RBF neural network (GA-RBF) optimization, trains the network by sampled data, and uses the trained network to reduce the positioning error noise. Finally, through the experimental verification, the optimization performance of GA-RBF and traditional RBF neural network algorithm was compared and analyzed.

II. UWB POSITIONING PRINCIPLE

The positioning method adopted by UWB is the positioning method based on the time of arrival (TOA). The principle is to use the TOA of the signal from the unknown node to the reference anchor point to calculate the distance between them. This method can make full use of the high temporal resolution of UWB signal at the receiving end. By detecting the signal delay, the distance from the node to the reference anchor point is estimated [6-7]. TOA-based positioning process can be split into two steps: First, the distance between the base station and the location tag is measured, which is calculated by the double-sided two-way ranging algorithm. The next step is to determine the coordinate position of the location tag, and to calculate the position coordinates of the tag by using the specific location algorithm through the measured distance information in the previous step.

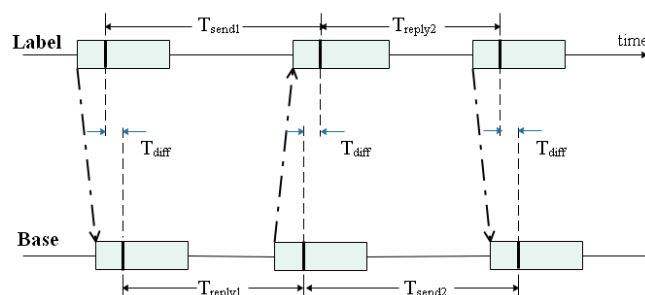


Figure.1 Principle of DS-TWR

Double-sided two-way ranging(DS-TWR) is an extended

ranging method of the single-sided two-way ranging, in which the signal flight time is determined by recording two round-trip time stamps. Compared with unilateral ranging, this method can greatly reduce the ranging error, even in the case of long response delay, the error will also be reduced [8-10]. The operation of DS-TWR is shown in Figure 1, after the Label is started, the Base completes the response and records the first round-trip measurement. Then the Base sends the signal Label to complete the response and records the second round-trip measurement. The signal transmission time can be calculated by formula (1). And the calculated time is multiplied by the signal transmission speed (the speed of light) to finish the complete DS-TWR exchange and algorithm calculation.

$$T_{diff} = \frac{(T_{send1} \times T_{send2} - T_{reply1} \times T_{reply2})}{(T_{send1} + T_{send2} + T_{reply1} + T_{reply2})} \quad (1)$$

TOA localization algorithm can locate the target in two-dimensional flat space by setting three or more base stations. Taking the positioning base station as the center, the position of the signal can be determined by making a circle with the distance between the measured signal source and each monitoring station as the radius. As shown in Figure 2, the intersection point M is the coordinate of the node to be solved.

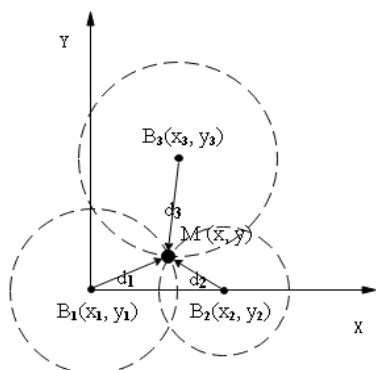


Figure.2 TOA positioning method

III. RADIAL BASIS NEURAL NETWORK

RBF neural network is a typical feedforward neural network. Similar to the multi-layer forward network, its structure is a three-layer forward network. A typical RBF neural network can be divided into three layers: input layer, hidden layer and output layer. As shown in figure 3, in RBF neural network, the main function of input layer is to acquire and transmit data; the hidden layer is responsible for adjusting the parameters of the activation function, and the nonlinear function is used to optimize the parameters of the layer; at the output layer, the best prediction result is output by adjusting the weights of each node.

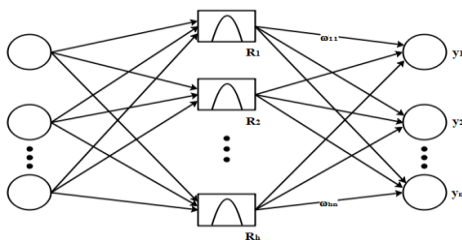


Figure.3 RBF neural network structure

Three parameters are required for RBF neural network learning process: the basis function center, the variance and the weight from the hidden layer to the output layer. The learning algorithm of RBF network includes two stages: self-organizing learning and tutorial learning, the former is used to solve the center and variance of the basis function, and the latter is used to solve the weight between the hidden layer and the output layer.

The hidden layer commonly uses gaussian function as the basis function in RBF neural networks, and its activation function is often expressed as formula (2):

$$R(x_p - c_i) = \exp\left(-\frac{\|x_p - c_i\|^2}{2\sigma^2}\right) \quad (2)$$

Where $\|x_p - c_i\|$ is the Euclidean norm, c_i is defined as the center of the gaussian function, and σ is the variance of this function.

Back to the structure of RBF neural network shown in Figure 3, the output of this network can be represented by the following formula.

$$y_j = \sum_{i=1}^h \omega_{ij} R(x_p - c_i) \quad j = 1, 2, \dots, n \quad (3)$$

In this formula, $x_p = (x_1^p, x_2^p, \dots, x_m^p)^T$ is the input sample, ω_{ij} is the connection weight, i represents the number of hidden layer nodes, and y_i corresponds to the output of each output node.

Assuming that d is the expected output of the network, the variance of the basis function can be represented by formula 4.

$$\sigma = \frac{1}{P} \sum_j^m \|d_j - y_j c_i\|^2 \quad (4)$$

IV. GA-RBF NEURAL NETWORK POSITIONING ALGORITHM

A. Using Genetic algorithm Calculate the RBF's center value

The calculation process of genetic algorithm is to encode the selected hidden layer central value into a symbol string, namely, chromosome. On the basis of the original chromosome, selection, crossover, mutation and other operations are performed according to the fitness function to produce more excellent individuals. With the increase of the number of heredity, the global optimal solution can be found more quickly by searching the solution space in parallel, thus optimizing the central value of RBF neural network activation function [11-12].

GA-RBF neural network algorithm process includes three parts: determine the network structure of RBF neural network, optimize the parameters by the genetic algorithm and train the network. As shown in Figure 4, the number of hidden layer units determines the structure of the RBF neural network, thus come to decision the chromosome length of the individual by the genetic algorithm, and each string

corresponds to the center of an RBF activation function. Every individual in the population contains all the weights and center points of a network. Individuals calculate their fitness values through fitness function. Genetic algorithm seek out the individual corresponding to the optimal fitness value through selection, crossover and mutation operations, and then optimizes the weights and center points of RBF neural network. In the prediction part of RBF neural network, genetic algorithm is used to get the initial weight and center value of the optimal individual, and the final network is trained to predict the output of the network.

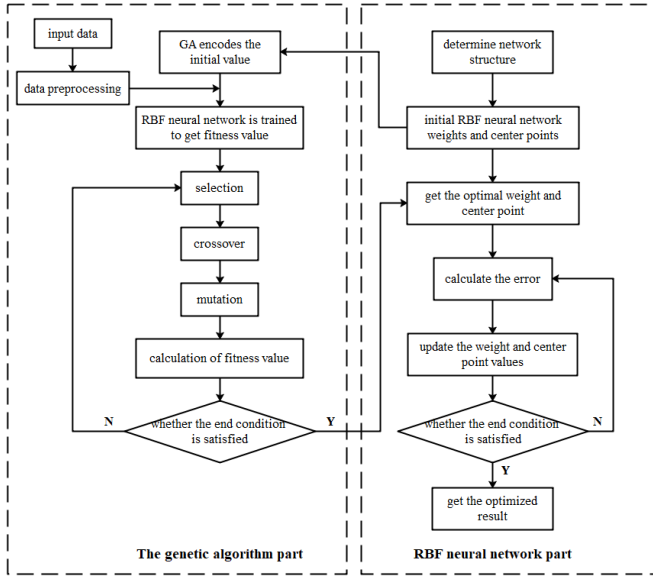


Figure.4 Algorithm flow chart

In the evolutionary search, genetic algorithm is always based on the adaptation function, so the selection of the fitness function is very important, which will directly affect the convergence rate of the algorithm and whether the optimal solution can be found as soon as possible. Considering about the hidden layer element point (x_i, y_i) , then weight ω and center point c can be obtained by the minimization function, as shown in formula 5.

$$f(\omega, c) = \sum_{i=1}^n (y_i - f(x_i))^T (y_i - f(x_i)) \quad (5)$$

Where y_i is the approximate value and $f(x_i)$ is the network output.

B. Position algorithm based on GA-RBF neural network

In the ideal zero-mean gaussian distribution environment without the influence of line-of-sight errors, the TOA algorithm can achieve high positioning accuracy, but the positioning accuracy of the algorithm becomes poor in the non-line-of-sight(NLOS) environment. Using the trained GA-RBF neural network to optimize TOA ranging can significantly suppress the error caused by NLOS and improve the accuracy of indoor wireless positioning. The specific positioning process is shown in Figure 5.

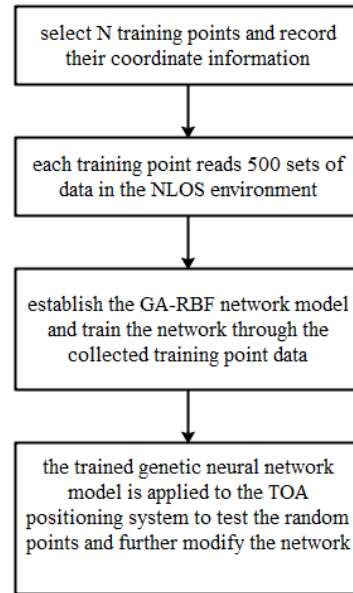


Figure.5 Genetic Neural Network Positioning flow chart

1) Select N representative training points in the indoor environment (the regions with greater influence of NLOS have higher density) and record their accurate location information, so as to ensure that the neural network can fully learn the characteristics of the environment.

2) For the selected training points, use TOA algorithm to locate and record 500 groups of data at each point to train GA-RBF network.

3) Establish the GA-RBF network model and train the network with the data collected from the training points.

4) The trained GA-RBF neural network model was applied to the UWB positioning system, and a large number of random point tests were conducted to further verify and modify the network.

V. EXPERIMENTAL RESULTS AND ANALYSIS

The experimental site is $14m \times 12m \times 4m$ flat horizontal area in graduate student laboratory of department of electrical science, Shandong University of Science and Technology. Using the horizontal plane where the node to be located is the x-o-y plane to establish a two-dimensional rectangular coordinate system, the x and y coordinates of the node to be located are analyzed in the experiment, as shown in figure 6. Without the optimization algorithm, due to the influence of hardware and indoor environment, UWB positioning error can reach about 1m, which is displayed as a gaussian distribution around the true value.

Using orthogonal least squares method build a traditional RBF neural network, and the hidden layer was set as 52 neurons. Then the traditional RBF neural network was trained and tested with the sample data collected from the experiment, and the traditional RBF neural network model is established. In order to compare the positioning efficiency of the traditional RBF and the GA-RBF, several static points are selected for testing. The positioning effect is shown in figure 7.

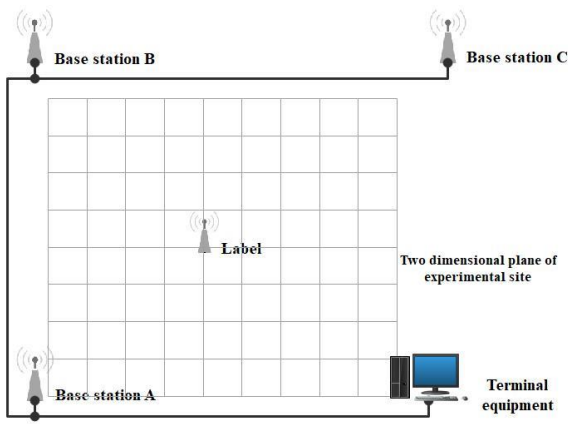


Figure.6 Schematic diagram of experimental site

Figure 8 compares the mean square error of using RBF neural network alone and using GA-RBF neural network. It can be seen clearly that the GA-RBF not only improves the positioning stability, but also greatly improves the positioning accuracy. The positioning means square error optimized by the GA-RBF algorithm limited in 3×10^{-3} , and the optimization effect is very obvious.

Figure 9 shows the error cumulative distribution function (CDF) in the experiment, where abscissa represents positioning error and ordinate represents cumulative distribution function. The yellow line in the figure is the result of the cumulative error distribution of GA-RBF algorithm proposed by this paper. It can be seen that the positioning accuracy optimized by GA-RBF algorithm is relatively high, and error is less than 10cm.

It can be seen that using the same ranging data, the positioning error of GA-RBF neural network algorithm is much smaller than that of traditional RBF neural network. GA-RBF neural network overcomes the oscillation problem caused by the uncertainty of initial weight and center point of traditional RBF neural network. Therefore, GA-RBF neural network algorithm has better positioning optimization performance.

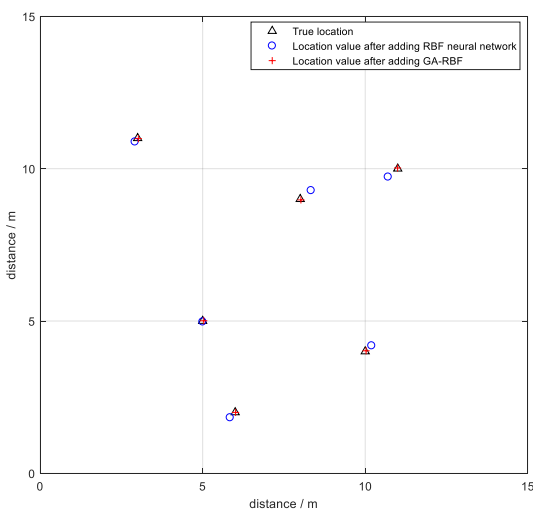


Figure.7 Positioning effect

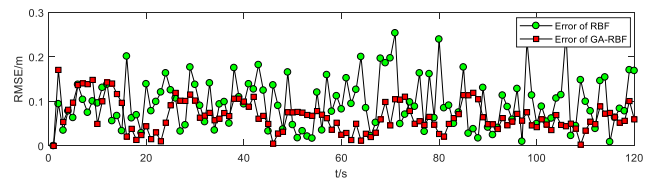


Figure.8 Comparison of mean square error between two algorithms

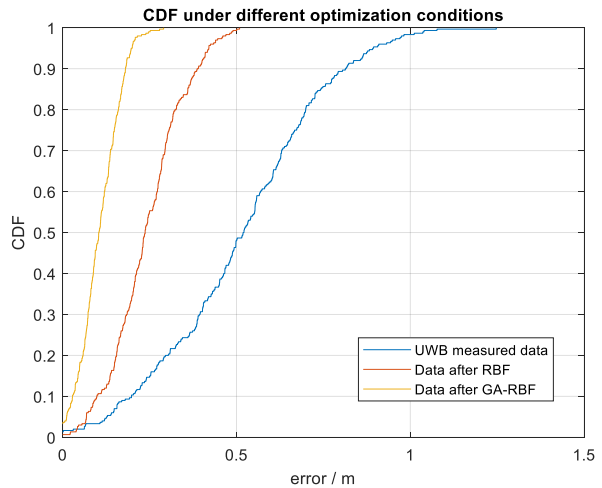


Figure.9 Cumulative distribution function of positioning errors

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