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A Node Localization Algorithm based on Woa-Bp Optimization

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Abstract: With the rapid development of 5G technology, the era of interconnection of all things has arrived. At the same time, a variety of hardware and software are getting more and more location information through sensors, and the accuracy of location information is increasingly important. Because traditional positioning relies on satellite signals, it achieves good results outdoors without obstruction, but indoors, due to the obstruction of various walls, such as Beidou satellite navigation system and U.S. Global Positioning System, it is difficult to meet the accuracy requirements for indoor positioning. Therefore, how to improve the positioning accuracy of indoor nodes has become a research hotspot in the field of wireless sensor. In order to improve the indoor positioning accuracy, this paper combines artificial neural network, intelligent optimization algorithm and node positioning to improve the accuracy of indoor positioning. One of the essences of the neural network is to solve the regression problem. Through the analysis of indoor node positioning, it can be concluded that the accuracy of distance-based positioning method lies in finding the relationship between signal strength and distance value. Therefore, the neural network can be used to regression analysis of signal strength and distance value and generate related models. In order to further improve the accuracy and stability of indoor node positioning, a method combining whale optimization algorithm with neural network is proposed. By using the whale optimization algorithm to find the optimal parameters of the neural network model, the training accuracy and speed of the neural network are improved. Then, using the excellent fitting ability of the neural network, the mapping relationship between RSSI value and distance value of indoor nodes is fitted, and the corresponding regression analysis model is generated, which can minimize the noise problem caused by abnormal signal attenuation and reduce the indoor positioning error. Finally, the data is processed by the neural network to get the parameters needed in the positioning algorithm. The experimental results show that the node positioning model based on the optimized neural network and the single optimization algorithm has significantly improved the positioning accuracy and stability.

Index Terms: Internet of things; indoor positioning; whale optimization algorithm; BP neural network.

1. Introduction

In recent years, with the maturity of wireless sensor network and the popularity of various intelligent devices based on wireless network, most of the related services of intelligent devices rely on accurate location information, however, the inaccurate location information of intelligent devices affects the intelligence of products. In order to improve the usability and use experience of products, many product manufacturers have invested considerable capabilities to improve the accuracy and stability of equipment positioning [1-5]. Thus, it is very important for the intelligent device to get the position of intelligent device accurately. Finding a precise, reliable and low-cost indoor positioning method has great commercial value and development prospects, which is one of the research directions of many scholars in recent years. Most intelligent equipment is facing the commercial, service and household consumption markets, and its use scenarios are mostly in relatively closed rooms. The weakening ability of satellite signal is strong, and it cannot rely on the satellite signal of the existing system to locate the equipment, which makes it difficult to locate. At present, the positioning system with excellent positioning capability, such as Beidou satellite navigation system, which has the highest global positioning accuracy, has a positioning accuracy of less than 10 meters under the condition of relatively open outdoor and less shelter. However, for indoor positioning requirements, it is usually necessary to accurately locate to "meter level" or even "cm level". For example, the sweeping robot accurately generates the house type map when it is first used, and accurately locates the position of itself during the use; the feeding robot can accurately locate the table according to the task requirements when performing the meal delivery task; in the case of the machine, it can be accurately positioned to the designated table according to the task requirements; in the case of the table, the robot can

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accurately locate the table according to the task requirements; in the case of the table, the robot can accurately generate In case of fire scene with extremely poor conditions, the trapped personnel shall be accurately positioned according to the equipment worn to facilitate rescue by rescue members; in case of large underground parking lot and loss of satellite positioning assistance, it can accurately locate the position of the required vehicle, establish the route behavior of mobile equipment to vehicle, and generate navigation line. These practical application scenarios need to rely on high-precision location information, but these intelligent devices often because of the inaccurate positioning information and the relative aging of technology, which leads to the signal transmission blocked by obstacles, so that they cannot accurately obtain the required position information and fulfill their task requirements. Therefore, in the case that the original outdoor positioning system has lost its accuracy, we need to find a fast, stable, reliable and accurate indoor positioning method, so that intelligent equipment can be widely used and the use experience of intelligent equipment can be improved [6-9].

With the development of swarm intelligence optimization algorithm and the application of neural network, more and more researchers begin to combine the optimization algorithm and neural network to establish the corresponding data model, which can more accurately reflect the correlation between data and data, reduce the signal attenuation problem caused by the complex indoor environment, so as to reduce the positioning error and improve the indoor positioning accuracy The accuracy and stability of positioning can meet the actual needs of indoor positioning with high accuracy.

2. Related Work

As another important part of indoor positioning field, indoor positioning algorithm plays an important role in the positioning accuracy of nodes. Appropriate positioning algorithm can effectively reduce the cost and improve the positioning accuracy. At present, there are many classification methods of indoor positioning algorithm. Based on whether it is necessary to measure the distance between the target node and the reference node, it is mainly divided into two categories. One is based on non-measurement distance. The other is location algorithm based on measurement distance [10].

RSSI positioning algorithm is commonly used in indoor positioning, and it is also an algorithm with better positioning effect. Compared with the first three algorithms, the positioning process of RSSI is simpler and easier to master and understand. There is a relationship between the transmitting power and the receiving power of the core wireless signal in formula (1).

$$\mathrm{P_r} = \mathrm{P_t} \div \mathrm{d^n} \tag{1}$$

Among them, $\mathrm{P_r}$ is the received power of the wireless signal, $\mathrm{P_t}$ is the transmission power of the wireless signal, the unit of the two transmission powers is MW, d is the distance between the wireless signal transmitting device and the receiving device, n is the propagation factor, and the value depends on the propagation environment of the wireless signal.

By logarithm operation on both sides of formula (1), formula (2) can be obtained

$$n * \log_{10} d = \log_{10} P_t - \log_{10} P_r \tag{2}$$

From the common sense of physics, we can see that the unit of signal strength is decibel milliwatt (DBM), and the relationship between signal strength and any power P satisfies the formula (3)

$$x = 10 * \log_{10} P \tag{3}$$

x is the signal strength. At this time, according to the conversion relationship of formula (3), we can introduce a constant A, which represents the power of wireless signal transmission at a distance of 1 meter. Because of the noise in the process of signal propagation, the noise variable X_σ is introduced. Then $\mathrm{P_r}$ Then we can deduce the formula (4)

$$P_r(dBm) = A - 10 * \mathrm{n} * \log_{10} d + X_\sigma \tag{4}$$

From formula (4), we can get the conversion formula between distance and RSSI value:

$$d = 10^{\frac{|RSSi| - A - X_\sigma}{10n}} \tag{5}$$

It can be seen that the relationship between the received signal strength and the signal transmission distance depends on the constants A and n. The smaller the propagation factor n and the appropriate signal power constant A can increase the signal propagation distance. The closer the experimental wireless signal propagation curve is to the theoretical curve, the more accurate the RSSI based ranging will be. When the unknown node gets the distance value to the three anchor nodes through calculation, the coordinates can be obtained through trilateral positioning method.

3. Method

In Whale optimization algorithm is a meta heuristic optimization algorithm proposed by mirjalili and Lewis. The algorithm constructs a mathematical model based on the simulation of two kinds of hunting modes of humpback whales, which has three modes: encircling predation, bubble predation and random mutation. In this algorithm, it is usually assumed that the whale population size is N, and the appropriate population size is helpful to improve the optimization speed of the whole algorithm[11-17]. The dimension of the optimization problem to be solved is D, that is, the dimension of the variable space is D. D can also be regarded as the number of variables. The position of each body i in the variable space is $\overline{X_i} = (x_i^1, x_i^2, \cdots, x_i^D)$, where $i = 1,2,\cdots,N$, the position of each individual is the candidate solution space, and the current optimal solution is the position of the current optimal individual. If the number of iterations exceeds or there is no better optimal solution, the current optimal solution is the global optimal solution.

By simulating the way of humpback whale predation, when the target location is uncertain, the algorithm assumes that the current optimal solution is the coordinates of the whale closest to the target, and sets it as the search agent or the leading whale. Other whales will approach according to this location to achieve the goal of encircling the target. In this process, the whale first calculates the distance between itself and the leading whale, mainly through formula (6).

$$\vec{D} = \left|\vec{C} * \overrightarrow{X^*}(t) - \vec{X}(t)\right| \tag{6}$$

In the formula, $\vec{D}$ is the distance between the current whale and the leading whale, $\vec{C}$ is the coefficient vector, t is the current number of iterations, $\overrightarrow{X^*}$ is the position of the current leading whale, and $\vec{X}$ is the position of the current whale. In this case, the coefficient vector $\vec{C}$ can be calculated by formula (7).

$$\vec{C} = 2 * \vec{r} \tag{7}$$

$\vec{r}$ is a random number with uniform distribution and its distribution interval is between $[0,1]$. At this time, we have completed the calculation of the distance between our own whale and the leading whale, and then we update the position of our own whale through formula (8) to make our position close to the leading whale, so as to encircle the prey.

$$\vec{X}(t+1) = \overrightarrow{X^*}(t) - \vec{A} * \vec{D} \tag{8}$$

$\vec{X}(t+1)$ represents the position of the whale itself after the current iteration. A is also a coefficient vector, and its calculation formula is formula (9).

$$\vec{A} = 2 * \vec{a} * \vec{r} - \vec{a} \tag{9}$$

$\vec{A}$ is a linear decreasing variable. According to the current number of iterations and the maximum number of iterations, the change curve is from 2 to 0.

In order to simulate this behavior, the algorithm uses formula (10) to represent the behavior that the whale spirals to update its position according to the position of the optimal solution.

$$\vec{X}(t+1) = \overrightarrow{D'} * e^l * \cos(2 * \pi * l) + \overrightarrow{X^*}(t) \tag{10}$$

In this formula, e is a natural constant, l is a random number between $[-1,1]$, and $\overrightarrow{D'}$ is the distance between the current whale and its prey. Therefore, in the above formula, we should first calculate the distance between the whale and its prey $\overrightarrow{D'}$ as follows:

$$\overrightarrow{D'} = \left|\overrightarrow{X^*}(t) - \vec{X}(t)\right| \tag{11}$$

In order to avoid falling into the local optimal value, the algorithm will randomly change its position through the position of other whales to search globally. The process is to calculate the distance between itself and a random whale in the population.

$$\vec{X}(t+1) = \overrightarrow{X_{rand}} - \vec{A} * \left(\left|\vec{C} * \overrightarrow{X_{rand}} - X(t)\right|\right) \tag{12}$$

In formula (12), $\overrightarrow{X_{rand}}$ is the position of a random whale in the population. It is necessary to explain formula (12). The use condition of the formula depends on the value of $\vec{A}$ When $\vec{A} > 1$ or $\vec{A} < 1$. The whale algorithm uses formula (12) to update its position. When $\vec{A} < 1$ and $\vec{A} > 0$, the whale algorithm uses formula (8) to update its position.

BP neural network belongs to a group of neural network models. It is a multilayer feedforward network trained by error back propagation[18-20]. It is widely used in the fields of classification, recognition, regression, compression and so on. It is one of the most widely used neural network models. BP neural network model mainly adopts three-layer structure, which are input layer, hidden layer and output layer. The neurons in each layer are independent of each other, and the signal is transmitted in one-way. The state of neurons in the input layer only affects the state of neurons in the hidden layer, which in turn affects the state of neurons in the output layer.

We assume that the network structure of BP neural network has d input neurons, l output neurons and q hidden layer neurons. Given the training set $D = \{(x_1, y_1), (x_2, y_2), \cdots (x_m, y_m)\}, x_i \in R^d, y_i \in R^l$, that is, the input data is composed of d attributes, and the l-dimensional real value vector is output. The threshold of the j-th neuron in the output layer is expressed by θ_j. The threshold of the h -th neuron in the hidden layer is expressed by γ_h. The weight v_{ih} of the i-th neuron in the output layer and the h-th neuron in the hidden layer. The weight w_{hj} of the h-th neuron in hidden layer and the j-th neuron in hidden layer. In this case, the input signal received by the h -th neuron in the hidden layer is represented by formula (13).

$$\alpha_h = \sum_{i=1}^{d} v_{ih} * x_i \tag{13}$$

The input signal received by the j-th neuron in the output layer is expressed by formula (14)

$$\beta_j = \sum_{h=1}^{q} w_{hj} * b_h \tag{14}$$

b_h is the output of the h-th neuron in the hidden layer. For the samples in each training set, BP algorithm first obtains the training samples from the given data set D, and at the same time obtains the learning rate η. Then, the ownership value and threshold value in the network are initialized randomly within the range of $(0,1)$, and the output y of the current sample is calculated according to the parameter value set by the current BP neural network and formula (15).

$$\hat{y}_j^k = f(\beta_j - \theta_j) \tag{15}$$

f is the set activation function. According to formula (14), the BP neural network is obtained in the data set (x_k, y_k) the mean square error on is:

$$E_k = \frac{1}{2} \sum_{j=1}^{l} (\hat{y}_j^k - y_j^k) \tag{16}$$

y_j^k the expected output value of the current sample. Then we calculate the gradient term g_j of neurons in the output layer according to formula (17).

$$g_j = -\frac{\partial E_k}{\partial \hat{y}_j^k} * \frac{\partial \hat{y}_j^k}{\partial \beta_j} = \hat{y}_j^k (1 - \hat{y}_j^k)(y_j^k - \hat{y}_j^k) \tag{17}$$

In the phase of back propagation, the algorithm needs to calculate the gradient value of hidden layer neurons according to formula (18):

$$e_h = -\frac{\partial E_k}{\partial b_h} * \frac{\partial b_h}{\partial \alpha_h} = b_h (1 - b_h) \sum_{j=1}^{l} w_{hj}\, g_j \tag{18}$$

Finally, the weight value w_{hj} and v_{ih}, threshold value θ_j and $\gamma_h$in the algorithm are calculated by the error of hidden layer neurons calculated by formula (18).

$$\Delta w_{hj} = \eta * g_j * b_h \tag{19}$$

$$\Delta v_{ih} = \eta * e_h * x_i \tag{20}$$

$$\Delta \theta_j = -\eta * g_j \tag{21}$$

$$\Delta \gamma_h = -\eta * e_h \tag{22}$$

When some termination conditions are reached, BP algorithm stops automatically.

4. Using Woa-Bp to Optimize Indoor Environment Attenuation Model

In this paper, the optimization ability of WOA and the nonlinear mapping characteristics of BP neural network are used to fit the relationship between RSSI value and distance. WOA algorithm is combined with BP neural network, and WOA algorithm is used to adjust the parameters of BP neural network. Then the RSSI value data and corresponding parameters collected at different distances are taken as the input value of BP neural network, and the coordinates of unknown nodes are taken as the output value of BP neural network, so as to establish WOA-BP neural network model and complete the node positioning[21-26].

The quality of BP neural network model is related to the number of hidden nodes to a certain extent. The number of hidden layer nodes is also called the number of hidden layer neurons. Choosing the appropriate number of layers and hidden layer nodes will affect the performance of neural network to a great extent. Too few neurons in the hidden layer will lead to "under fitting" phenomenon. On the contrary, using too many neurons may lead to over fitting. When the neural network has too many nodes (too much information processing ability), the limited amount of information contained in the training set is not enough to train all the neurons in the hidden layer, so it will lead to "over fitting". Even if the training data contains enough information, too many neurons in the hidden layer will increase the training time, so it is difficult to achieve the desired effect. Kolmogorov theorem proves that as long as a hidden layer contains enough neurons, it can be a continuous function that makes neural network approach any complexity with any precision. So, it is very important to choose an appropriate number of neurons in the hidden layer. According to the test, when the number of hidden layer neurons is 13, the error result is the smallest, which is better than the number of other hidden layer nodes. The number of layers and nodes of WOA-BP neural network is input hidden output layer, and the number of neurons in each layer is 2, 13 and 2 respectively.

Activation function is a function used to calculate the weighted sum of input and deviation in neural network, which is used to determine whether neurons can be released. It usually manipulates the data by some gradient processing of gradient descent method, and then produces the output of neural network, which contains the parameters in the data. Through the test, in WOA-BP neural network, choosing tanh function as the activation function of neural network can make the model error minimum.

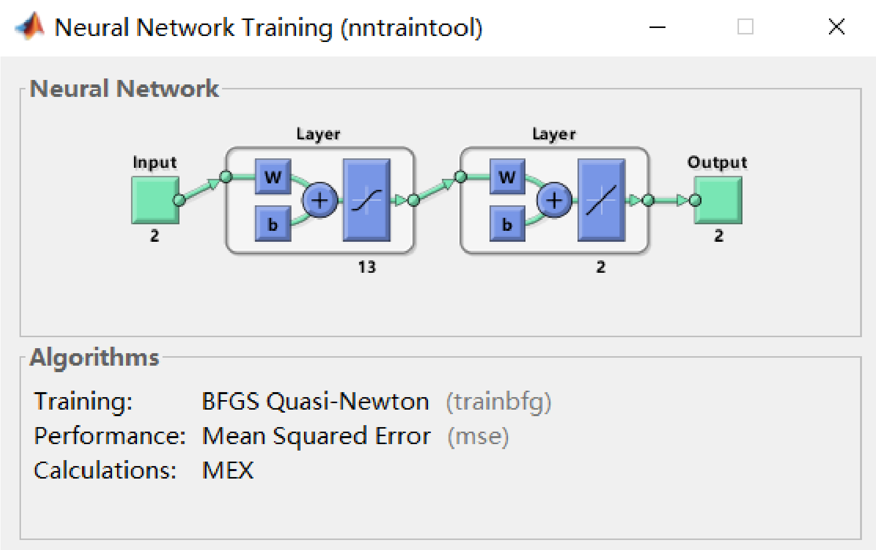

Fig. 1. WOA-BP model structure diagram

The difference between BP neural network and other neural network models is that BP neural network is a kind of multilayer feedforward network trained by error back propagation. Error retransmission is to retransmit the output error layer by layer through the hidden layer to the input layer, and allocate the error to all units of each layer. The error signal obtained from each layer is used as the basis for adjusting the weight of each unit, so it is necessary to use the training function to complete the error retransmission. Through the test, the trainbfg function is selected as the back-propagation training function.

Figure 1 shows the network structure of WOA-BP neural network model. WOA-BP neural network mainly uses the RSSI value of known AP nodes as the input value, and the two-dimensional plane coordinates of the points to be measured as the output feature to establish the BP neural network model. Then, according to the ratio of 7:3, the data is divided into training set and verification set. The training set is used for the training of BP neural network model. After the establishment of BP neural network model, the test set is used to verify the feasibility of the network. Then normalize the data, and set the neural network maximum training times, training accuracy, learning rate, maximum failure times, transfer function, training function, initial threshold, initial weight and other related parameters. Then, using the optimization ability of WOA, the parameters suitable for the neural network under the data set are found, and the optimal parameters are returned to the BP neural network model. When the training process is finished, the error is less than the set value. Then use the test data to verify whether the network model is the optimal model, if it is to save the BP neural network model, otherwise the model is trained again.

5. Experiments

In order to verify the positioning performance of WOA-BP neural network model in indoor positioning field, MATLAB r2019a is used to carry out simulation experiment, and the model is compared with the unmodified BP neural network model. The neural network model with the least training error is selected. In order to be more in line with the actual situation of indoor positioning, the positioning area is selected in a 10m × 10m square area. Several unknown nodes and known nodes are distributed in the region, and all the unknown nodes can obtain the communication signals of the known nodes.

In order to verify the positioning effect of WOA-BP neural network model, two models in the experiment are randomly selected for the coordinate data of the same positioning point. The coordinate point position and positioning effect are shown in Figure 2.

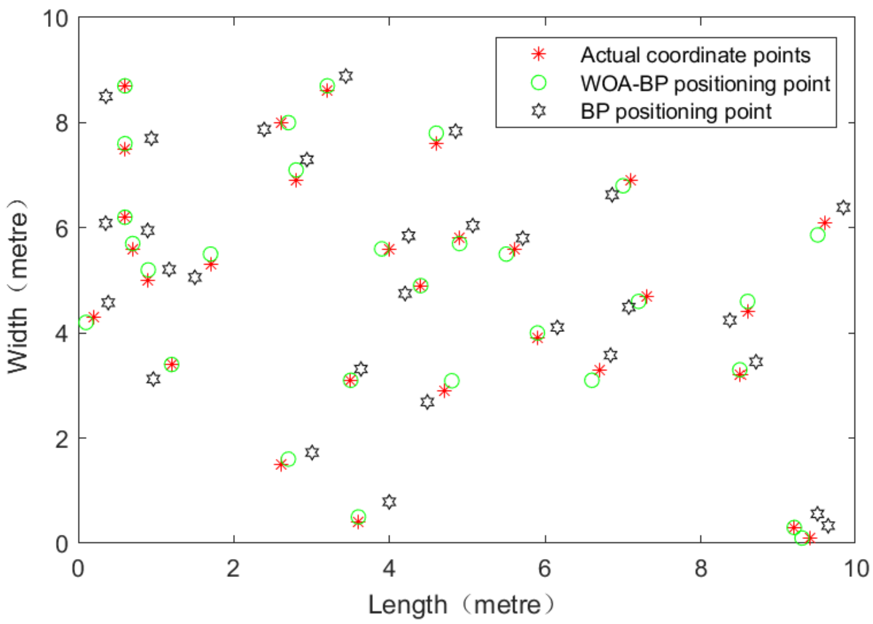

Fig.2. Schematic diagram of positioning coordinates

It can be seen from the figure above that although the coordinates calculated by WOA-BP neural network have some errors, the coordinates calculated by WOA-BP neural network are closer to the actual coordinates than those calculated by BP neural network. From another point of view, the fitting effect of WOA-BP neural network for indoor wireless signal attenuation curve is better than that of BP neural network, and the anti-noise ability is stronger. The BP neural network model optimized by WOA has higher accuracy in calculating coordinates and more accurate positioning accuracy.

In order to evaluate the relationship between positioning accuracy and running time of the two models. When the program is running, the running time and accuracy of the algorithm are recorded by introducing time tags. Finally, the positioning accuracy and running time are plotted in the chart. The experimental results are shown in Figure 3.

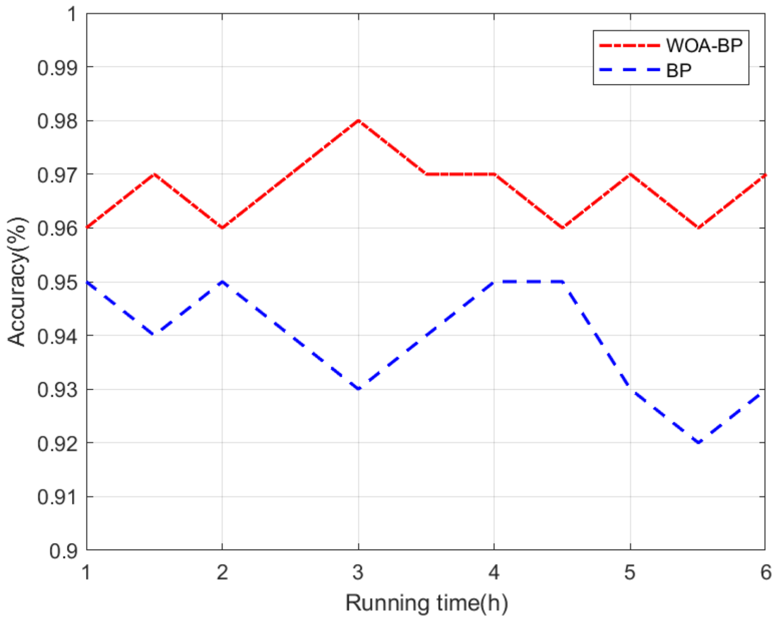

Fig. 3. Relationship between positioning accuracy and running time

It can be seen from the above figure that the positioning accuracy of neural network in indoor positioning is high, which is due to its strong mapping ability to nonlinear function, which can more accurately reflect the attenuation curve of wireless signal. However, different neural network models have some differences in positioning accuracy. The positioning accuracy of WOA-BP neural network model is about 97%, and that of single BP neural network model is about 94%, which shows that the positioning accuracy of WOA optimized BP neural network model is better than that of BP neural network model, and the fitting effect is stronger. In addition, from the stability of the algorithm, the BP neural network model is more stable in the early stage with the increase of time, which ensures higher positioning accuracy. But in the later period, there was a great change. The reason for this phenomenon may be that the RSSI value obtained by a node deviates from the distance value, which reduces the positioning accuracy. The WOA-BP neural network model is relatively stable with the increase of time.

In order to compare the training time cost and positioning efficiency of the two models, the training time and coordinate positioning time are introduced as the criteria for comparison. The comparison results are shown in Table 1.

Table 1 Comparison table of training time and calculation time of model

Model name	Training time(min)	Computing time（s）	Average positioning accuracy
WOA-BP	17:06	157	96.7%
BP	23:56	143	93.9%

It can be seen from the comparison in the table that the training time of WOA-BP neural network model is shorter, about 17 minutes on average, and the training time of BP neural network model is slightly longer, about 24 minutes on average. The BP neural network model optimized by WOA has faster training speed. The reason for this phenomenon is that the introduction of whale optimization algorithm speeds up the adjustment speed of the whole neural network model parameters, thus shortening the training time. When the two models deal with the same location data, the calculation time of WOA-BP neural network model is longer than that of BP neural network model. This is because WOA improves the complexity of the whole algorithm, improves the performance and increases the amount of calculation. In addition, WOA-BP neural network model has certain advantages in the average positioning accuracy, and the best model parameters can be obtained through the parameter adjustment ability of WOA, so as to improve the anti-interference ability and positioning accuracy.

In order to verify the anti-jamming ability of the two models for noise, and verify the attenuation degree of the positioning performance of the algorithm in bad environment. Part of the data is processed, and Gaussian noise with mean square deviation is added to simulate the wireless signal strength in harsh environment. Then WOA-BP neural network model and BP neural network model use this data for indoor positioning. Finally, the error between the calculated coordinates and the actual coordinates is calculated. The experimental results are shown in Figure 4.

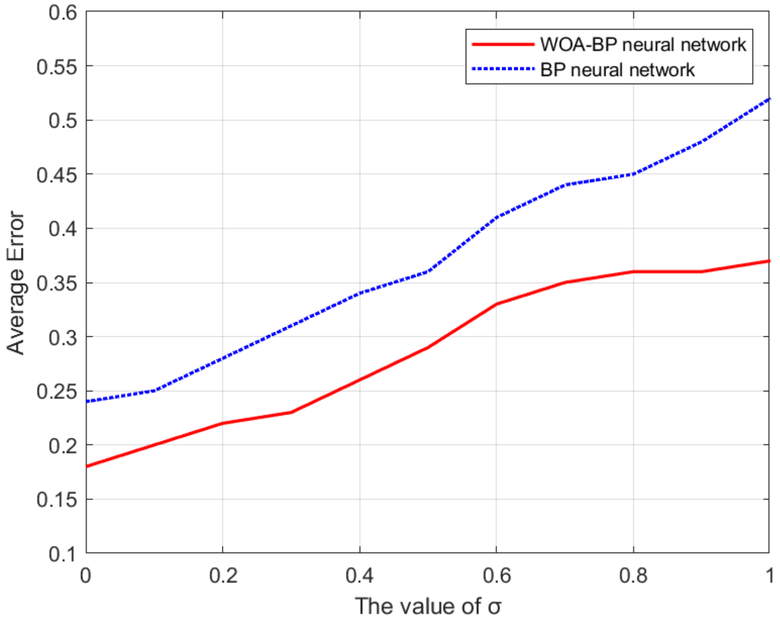

Fig. 4. Average error under different noise values

According to the figure above, we can see that the average error of WOA-BP neural network model and BP neural network model will increase with the increase of σ value. The BP neural network with WOA algorithm has better algorithm performance, so with the increase of σ value, it is relatively less affected, and its average error is relatively small. When the variance of σ value is between 0.6 and 1, the average error growth range of WOA-BP neural network is smaller than that of σ value between 0.2 and 0.6, which indicates that WOA-BP neural network has stronger anti-interference ability and stronger stability under high noise interference. On the contrary, the traditional BP neural network is relatively affected by noise, its average error is relatively high, and its positioning accuracy is worse than WOA-BP neural network. When the variance of σ value increases, its positioning accuracy will be greatly affected, and its stability is worse than WOA-BP neural network.

6. Conclusion

In this paper, a method combining WOA algorithm with BP neural network is proposed to locate unknown nodes. Through a variety of tests to determine the network structure of BP neural network, in order to achieve the optimization of neural network parameters. The optimization ability of WOA is used to train BP neural network model. Finally, the trained WOA-BP neural network model is used for simulation experiment. The experimental results show that the training time of the WOA optimized BP neural network model is less than that of the unoptimized BP neural network model, and the positioning accuracy is higher. And the BP neural network model optimized by WOA can still maintain high positioning accuracy under long-term operation. In conclusion, WOA-BP neural network has achieved good results in indoor positioning. However, this method still has some room for improvement, such as further shortening the training time and improving the positioning effect. This is the next direction of hard work.

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