Bluetooth Indoor Micro-positioning System based on Gaussian Filtering and Elman Neural Network

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***Abstract*—Due to the complex and diverse indoor environment, the traditional positioning algorithm used indoors will greatly reduce the positioning accuracy. Aiming at the ever-increasing demands of accuracy and stability in indoor positioning, an indoor micro-positioning system based on Bluetooth technology is designed. The low-power Bluetooth wireless data transmission module RL-CC2541-S3 is used as the signal acquisition unit, and the STM32F103ZET6 high-performance microprocessor is used as the core to complete the data processing and positioning calculation. An indoor positioning algorithm based on Gaussian filtering and Elman neural network is designed to improve the positioning accuracy of the system. Firstly, the Pauta criterion is used to eliminate the outliers of the sampled data to ensure the validity of the data. Then Gaussian filtering is used to remove the interference of Gaussian noise and the least squares method is used for curve fitting to further improve the accuracy of ranging. Finally, the nonlinear approximation of Elman neural network is used to achieve the target location. The experimental results show that the absolute error of indoor positioning is close to 0.3m, which is better than the traditional Chan algorithm, LS algorithm and Taylor series positioning algorithm, which can meet the needs of general indoor micro-positioning.**

Keywords—indoor positioning, Bluetooth, Elman neural network, Gaussian filtering

I. INTRODUCTION

In recent years, with the upgrade of consumption, there are more and more demand based on location services, such as logistics distribution, taxi software and so on. How to accurately obtain user location is critical to improving the quality of related services. Currently, the position information of the user can be obtained relatively accurately through the global positioning system (GPS) and the Beidou satellite navigation and positioning system in an outdoor environment. However, in the indoor environment, due to the occlusion of the building, etc., the positioning accuracy of the above positioning means is greatly reduced. How to accurately achieve indoor positioning is getting more and more attention. [1-2] At present, the commonly used indoor positioning methods include an indoor positioning method based on ultra wideband (UWB) technology, [3] an indoor positioning method based on Wi-Fi technology ,[4] an indoor positioning method based on radio frequency identification (RFID), [5] ZigBee-based indoor positioning method,[6] geomagnetic-based indoor positioning method ,[7] Bluetooth-based indoor positioning method, [8] etc.. Bluetooth-based indoor positioning method has the advantages of low power consumption and low cost, but there are still some shortcomings in positioning accuracy and positioning stability. Reasonable selection of appropriate indoor positioning algorithm has become a key factor to improve positioning accuracy. A. Ye et al. proposed an indoor positioning algorithm based on fingerprint recognition, [9] which improved indoor pedestrian positioning accuracy by modeling fingerprint and motion information as hidden Markov models. F. Liu et al. proposed an RFID positioning algorithm based on Glowworm Swarm Optimization (GSO) and semi-supervised online sequence extreme learning machine (SOS-ELM), [10] which automatically adjusts the regularization weight of SOS-ELM algorithm by GSO algorithm. It can quickly obtain the optimal regularization weight under different initial conditions, can obtain more accurate positioning results, and has certain adaptability to environmental changes. Z. Wang et al. proposed an AP positioning algorithm based on channel state information (CSI) sequence positioning (SBL-CSI) ,[11]the relative distance of the ordinary AP, served in the location sequence, is obtained by using CSI between the ordinary AP and special AP. The "nearest" feasible sequence of the ordinary AP in the location sequence table is searched, and the centroid of the corresponding region is the ordinary AP's localization. G. Gennarelli et al. used the inverse source method to describe the positioning problem as an imaging problem, [12]examining different measurement configurations and data processing strategies to study their positioning accuracy under line of sight (LOS) and non-line of sight (NLOS) conditions. X. Fang et al. proposed a multi-channel fingerprint localization algorithm for WSN in multipath environment.[13] Their proposed algorithm first uses an adaptive Kalman filter to reduce the noise in RSSI measured in different channels, and then calculates the matched fingerprint according to the weight of different channels. Finally, a memetic algorithm is utilized to generate the optimized estimate of fingerprint and location. J. Sun et al. proposed a three-dimensional positioning algorithm for indoor arrival time based on least squares and optimization algorithm, [14] which evaluates the performance of ranging and positioning accuracy through simulation and field test. X. Huang et al. proposed a hybrid fingerprint localization algorithm, [15] which combines CSI and magnetic field information to construct a fusion fingerprint database, and provides multidimensional scaling k-nearest neighbor (MDSKNN) method to achieve fingerprint matching. Y. Zhang et al. proposed a minimum residual localization algorithm based on particle swarm optimization.[16]By continuously optimizing and updating the particle swarm, the position of the best solution of the objective function is obtained as the final estimated position. In this paper, in order to solve the problem of insufficient positioning stability and accuracy of indoor positioning system based on Bluetooth technology, the low-power Bluetooth wireless data transmission module RL-CC2541-S3 is used as the signal acquisition unit, and the STM32F103ZET6 high-performance microprocessor is used as the core to complete the data processing and positioning calculation, an indoor micro-positioning system based on Bluetooth technology is designed. A localization algorithm based on Gaussian filtering and ELMAN neural network for indoor micro-positioning is proposed, which improves the positioning accuracy of the system and has certain adaptability to environmental changes.

II. Bluetooth Indoor Micro Positioning System

As shown in Fig. 1, the Bluetooth indoor micro-positioning system is composed of a system host, a Bluetooth anchor node and a positioning target, wherein the system host is composed of an embedded processor, a Bluetooth master node and a communication module. The embedded processor uses STMicroelectronics' STM32F103ZET6 high-performance microprocessor, the communication module uses SIMCOM's SIM900A module, and the Bluetooth module uses low-power Bluetooth wireless data transmission module RL-CC2541-S3. CC2541 is a 2.4GHz low-power Bluetooth chip produced by Texas Instruments. It integrates a high-performance low-power 8051 microcontroller core, supports the BLE protocol stack for Bluetooth applications and has a rich peripheral interface. The CC2541 can collect the received signal strength indication (RSSI) required for positioning, which improves the integration of the positioning anchor node and reduces the power consumption of the system. The SIM900A adopts an industry standard interface, and its working frequency is GSM 900/1800MHz. It can realize wireless transmission of data with low power consumption, and is mainly used for communication with the host computer. A Bluetooth module is fixed on the positioning target, and the system host and the Bluetooth anchor node are arranged in the located indoor area. For indoor planar positioning, the traditional three-point positioning algorithm requires at least one Bluetooth master node and two Bluetooth anchor nodes. The Bluetooth module fixed on the positioning target works in the host mode, and the Bluetooth master node and the Bluetooth anchor node work in the slave mode. The master node and the anchor node Bluetooth module respectively measure the received RSSI value, and send it to the master node through Bluetooth communication, and then the master node transmits the RSSI value of each node to the embedded processor through the communication interface. The embedded processor uses a positioning algorithm based on Gaussian filtering and Elman neural network to determine the location of the positioning target according to the RSSI value of each node. The system host can also communicate with the host computer through the communication module to transmit the location information to the host computer. If a more complex positioning algorithm is adopted, the embedded processor can also forward the RSSI value of each node to the upper computer, and the upper computer performs the calculation and analysis of the positioning.

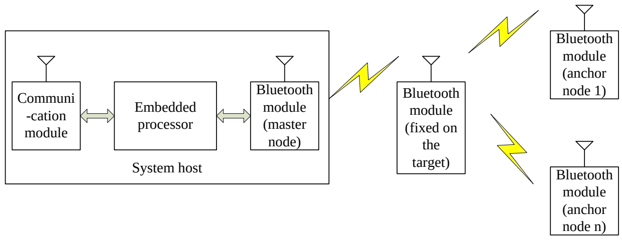

Figure 1. Bluetooth indoor micro positioning system.

III. Indoor Positioning Algorithm Based on Gaussian Filter and Elman Neural Network

A. Exclusion of Sample Data Outliers

In order to improve the positioning accuracy of the system, it is necessary to perform multiple sampling on the target positioning data, due to the large amount of sampled data in this system, the Pauta criterion is used to eliminate the outliers. Let the measured RSSI value be $x_i(i=1,2\cdots n)$, the mean value is $\overline{x}$, and the standard deviation is σ. If $x_i-\overline{x}>3\sigma$, then the suspicious value x_i contains coarse errors and should be discarded. If $x_i-\overline{x}\leq 3\sigma$, the suspicious value A is normal, it should be retained. After discarding the suspicious value, recalculate the mean and standard deviation of the other measurements that remove this value, and then continue to use this criterion to judge until all coarse errors are removed.

B. Gaussian Filtering and Least Squares Curve Fitting

A large number of experiments show that the random distribution of noise in the electronic system satisfies the Gaussian distribution. Gaussian filtering can effectively reduce the influence of this part of the random noise in the electronic system on the measurement, so as to remove the Gaussian noise component in the RSSI. The influence of the signal NLOS propagation and the like is retained as the positioning feature information. Since the position calculation in the system is completed by the embedded system, in order to reduce the amount of calculation, a Gaussian filtering algorithm with a simple algorithm is used for filtering, and a least squares curve fitting is used for curve fitting.

According to experience, the probability of selection of RSSI high probability is greater than 0.6. that is, available in Equation (1).

$$0.15\sigma+\mu<x<3.09\sigma+\mu \tag{1}$$

After Gaussian filtering, the RSSI range is shown in Equation (2).

$$[0.15\sigma_{RSSI}+\mu_{RSSI},3.09\sigma_{RSSI}+\mu_{RSSI}] \tag{2}$$

Among them: $\mu_{RSSI}=\frac{1}{N}\sum_{i=1}^{N}RSSI_i$

$$\sigma_{RSSI} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(RSSI_i - \mu_{RSSI})^2}$$

In order to further obtain the exact relationship between the RSSI value and the distance, the curve fitting is performed by the least squares method, and the fitted curve is an nth order polynomial, shown in Equation (3).

$$y = \sum_{i=0}^{n} a_i x^i \tag{3}$$

Expressed as a matrix: in Equation (4).

$$Y = X_0 A \tag{4}$$

Among them: $X_0 = \begin{bmatrix} x_1^n & x_1^{n-1} & \cdots & x_1^2 & x_1 & 1 \\ x_2^n & x_2^{n-1} & \cdots & x_2^2 & x_2 & 1 \\ & \vdots & \ddots & & \vdots & \\ x_k^n & x_k^{n-1} & \cdots & x_k^2 & x_k & 1 \end{bmatrix}$

$$A = [a_n, a_{n-1}, \cdots, a_2, a_1, a_0]^T$$

$$Y = [y_1, y_2, \cdots y_k]^T$$

The solution method of $Y = X_0 A$ is to multiply both sides of Equation to obtain Equation (5).

$$X_0^{\ T} Y = X_0^{\ T} X_0 A \tag{5}$$

Then both sides of Equation (8) are simultaneously multiplied by $(X_0^{\ T} X_0)^{-1}$ to get Equation (6).

$$A = (X_0^{\ T} X_0)^{-1} X_0^{\ T} Y \tag{6}$$

The parts on the right side of Equation (6) are known, so the coefficient vector A of the fitted curve equation can be directly solved. Then obtain the final RSSI value fitting curve according to Equation (4). According to the actual data test, when the current coefficient is equal to zero, the fitting ends, and the order of the fitting is 5th.

C. Indoor Location Algorithm Based on Elman Neural Network

The Elman neural network is a typical local regression network. It belongs to the feedback neural network. It is very similar to the forward neural network and has stronger computing power. Its outstanding advantage is that it has strong optimization calculation and associative memory function, and has the approximation function of nonlinear continuous rational function. When the actual environment changes greatly, the neural network needs to be trained to achieve a good positioning effect. The Elman neural network consists of an input layer, an implicit layer, and an output layer, and its connection rights can be corrected by learning. The feedback connection consists of a set of "structure" units that store the output values from the previous moment, and the connection weights are fixed. In this paper, the indoor positioning algorithm based on Elman neural network is used to make good positioning effect in complex indoor environment by comprehensively utilizing the measured RSSI measurement values of each node. The algorithm solves the problem that the least squares algorithm needs the prior information of the RSSI measurement value to construct the covariance matrix Q. At the same time, the algorithm eliminates the fuzzy problem of indoor positioning position and the influence of anchor node non-ideal distribution on positioning.

- Indoor positioning algorithm model based on Elman neural network

Fig. 2 shows an indoor positioning algorithm model based on Elman neural network. The Elman network consists of an input layer, a hidden layer, a receiving layer, and an output layer. The input layer consists of RSSI measurements provided by a Bluetooth master node and two or more Bluetooth anchor nodes. The input vector is shown in Equation (7).

$$In = [RSSI1, RSSI2, RSSI3 \cdots] \tag{7}$$

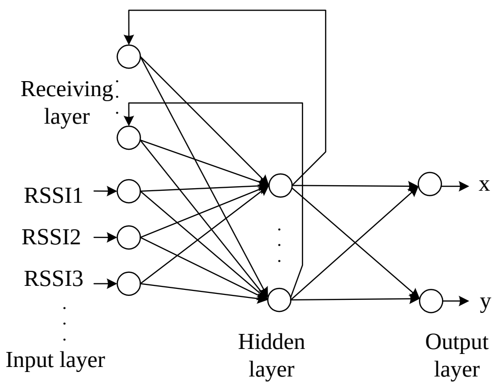

Figure 2. Indoor positioning algorithm model based on Elman neural network.

The number of hidden layer neurons can be obtained according to Kolmogorov's empirical formula for a three-layer neural network. The number of hidden layer neurons is $N_{hid} = 2N_{in} + 1$. N_{hid} is the number of hidden layer neurons. N_{in} is the number of input neurons. Increasing the number of hidden layer neurons can improve the positioning accuracy of the system, but it also increases the computational complexity. The system uses up to 8 Bluetooth nodes in the experiment, so the number of hidden layer neurons is 18. The output layer consists of two neurons whose output is the estimated position of the corresponding positioning target. The output vector is shown in Equation (8).

$$Output = [x, y] \tag{8}$$

- Elman neural network learning process

The state space equation of the Elman neural network is shown in Equation (9).

$$\begin{cases} y(k) = g(\omega^3 x(k)) \\ x(k) = f(\omega^1 x_c(k) + \omega^2(u(k-1))) \\ x_c(k) = x(k-1) \end{cases} \quad (9)$$

Among them:

y -m dimensional output node vector

x -n dimensional hidden layer node vector

u -r dimensional input vector

x_c -n dimensional feedback state vector

ω^3 -implicit layer to output layer connection weight

ω^2 -implicit layer to input layer connection weight

ω^1 -implied layer to socket connection weight

$g(.)$ -output layer transfer function

$f(.)$ -implicit layer transfer function

Where $g(.)$ is a linear transfer function, $g(x) = kx$. $f(.) = \frac{1}{1+e^{-x}}$. Let the actual output of the kth step system be $y_d(k)$, then the output error function can be expressed as Equation (10).

$$E(k) = \frac{1}{2}(y_d(k) - y(k))^T (y_d(k) - y(k)) \quad (10)$$

According to the gradient descent method, the partial derivative of the error function to the weight is calculated and made 0, and the correction value of each connection weight can be obtained and shown in Equation (11).

$$\begin{cases} \Delta\omega_{ij}^3 = \eta\delta_i^0 x_j(k) \\ (i = 1, 2, \cdots, m;\ j = 1, 2, \cdots, n) \\ \Delta\omega_{jq}^2 = \eta\delta_j^h u_q(k) \\ (j = 1, 2, \cdots, n;\ q = 1, 2, \cdots, r) \\ \Delta\omega_{jl}^1 = \eta\sum_{i=1}^{m}(\delta_i^0\omega_{ij}^3)\frac{\partial x_j(k)}{\partial\omega_{jl}^1} \\ (j = 1, 2, \cdots, n;\ l = 1, 2, \cdots, n) \end{cases} \quad (11)$$

Among them: $\delta_i^0 = (y_{d,i}(k) - y_i(k))g_i'(\cdot)$

$$\delta_j^h = \sum_{i=1}^{m}(\delta_i^0\omega_{ij}^3)f_i'(\cdot)$$

- Flow of indoor positioning algorithm based on Elman neural network

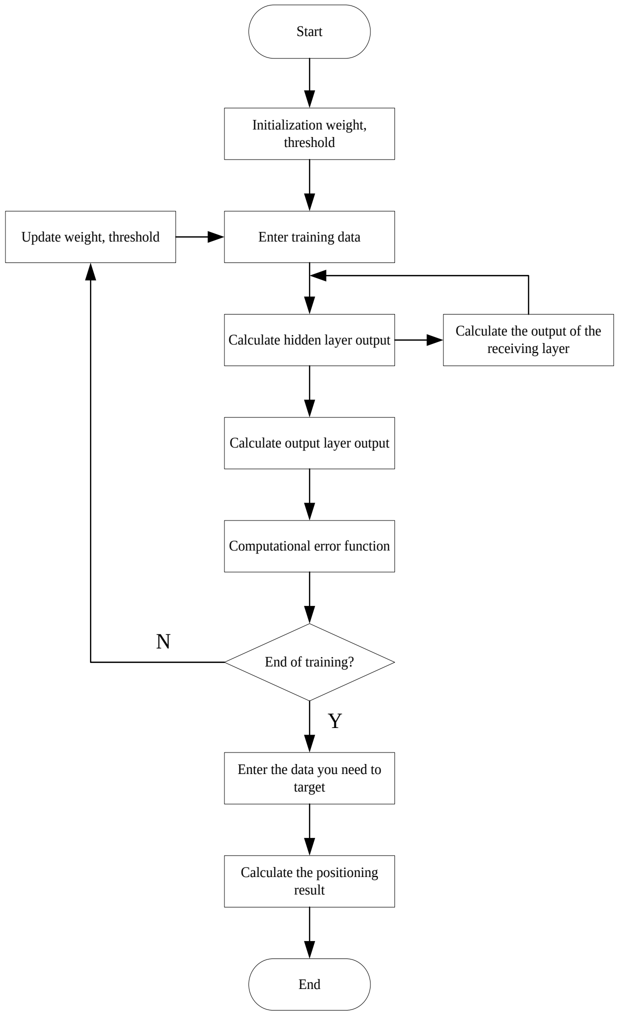

Figure 3. Process of indoor positioning algorithm based on Elman neural network.

The flow of the indoor positioning algorithm based on Elman neural network is shown in Fig. 3. First, the Elman neural network based indoor positioning algorithm model constructed according to Fig. 2 initializes the weight and threshold of the network. Then the data is measured to train the network. The training process is divided into two phases: (1) Calculate the output of the hidden layer and the output layer from front to back. (2) Calculate the iteration error from the back to the front, adjust the weight and threshold of the network according to the iterative error, and the training ends when the iteration error is less than the set threshold or exceeds the maximum number of iterations. After the training, the system stores the final determined network weight, and then the required positioning object can be positioned to determine the estimated position of the target. The accuracy of the positioning is evaluated by calculating the root mean square error RSME of the positioning. The method for calculating RSME in two-dimensional positioning estimation is shown in Equation (12).

$$RMSE = \sqrt{E[(x-\hat{x})^2 + (y-\hat{y})^2]} \qquad (12)$$

(x, y) is the actual location of the MS and $(\hat{x}, \hat{y})$ is the estimated location of the MS.

IV. Experimental Results and Analysis

Fig. 4 is the experimental scene. The Bluetooth module obtains the RSSI value every 0.1s.

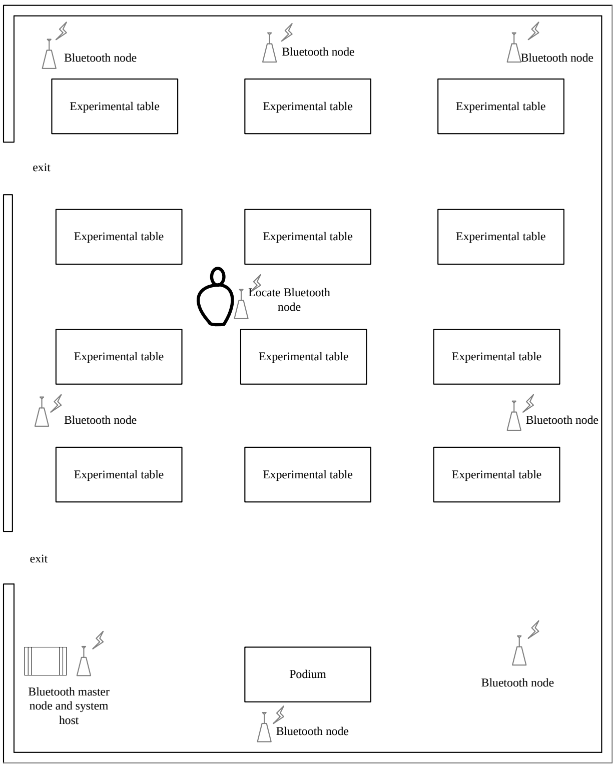

Figure 4. Positioning experiment plan.

Fig. 5 shows the relationship between the measured RSSI value and the distance. Each positioning point continuously acquires 200 RSSI values. For the collected data, the Pauta criterion is first used to eliminate the outliers. The data is then filtered by Gaussian filtering to eliminate Gaussian noise. In the experiment, 1000 anchor points were selected for data sampling and preprocessing, and then the Elman neural network was trained. After the training is completed, 1000 positioning points are selected for data sampling and processing. Then, the proposed algorithm and the traditional Chan algorithm, LS algorithm and Taylor algorithm are used to locate the target and analyze and compare the positioning results.

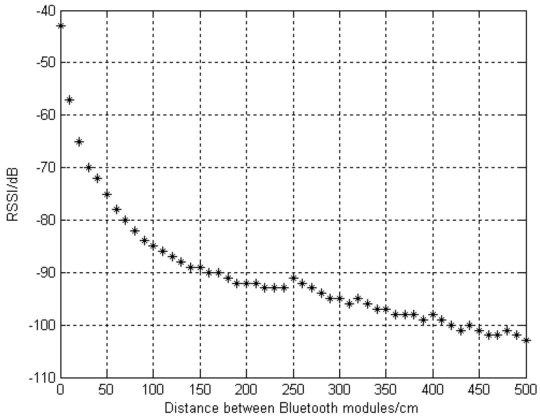

Figure 5. Measured RSSI value and distance relationship.

Fig. 6 shows the influence of the number of positioning nodes on the positioning error of Chan algorithm, LS algorithm, Taylor algorithm and Elman neural networks algorithm . It can be seen from the experimental results in Fig. 6 that with the increase of the number of Bluetooth positioning nodes, the root mean square error of the positioning decreases with the four algorithms. The reason is that the redundancy of the positioning information effectively reduces the positioning error. Among the four algorithms, the Chan algorithm has low positioning accuracy. This is because the Chan algorithm is based on the premise that the RSSI ranging error is small and the RSSI ranging is required to be an ideal zero-mean Gaussian random variable. Since the LS positioning algorithm does not consider the statistical characteristics of the RSSI ranging error, the positioning accuracy is better than the Chan algorithm. The Taylor algorithm has higher positioning accuracy in indoor environments, and the positioning accuracy is second only to the algorithm in this paper. The positioning accuracy of the proposed algorithm is obviously better than other algorithms, which eliminates the influence of ranging error and measurement error caused by indoor complex environment to a certain extent, thus improving the positioning accuracy, and the positioning accuracy can be close to 0.3m.

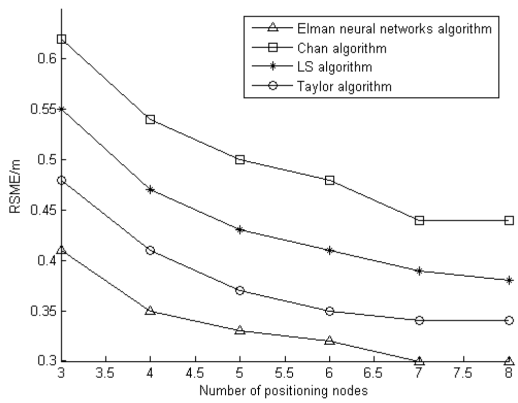

Figure 6. The influence of the number of positioning nodes on the average error.

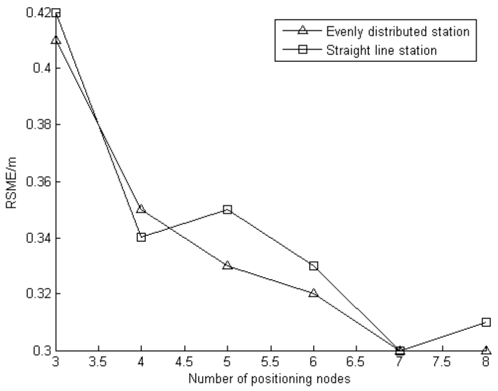

Figure 7. The effect of positioning node layout on the average error.

Fig. 7 shows the experimental results when the positioning nodes are arranged in a straight line. It can be seen from Fig. 7 that the linear positioning of the Bluetooth positioning node and the uniform distribution of the Bluetooth positioning node (as shown in Fig. 4) are similar when using the indoor positioning algorithm based on the Elman neural network. This is because the indoor positioning algorithm based on Elman neural network has strong ability to approximate arbitrary nonlinear mapping, which makes it suitable for non-ideal base station distribution forms, and effectively meets the requirements of positioning accuracy.

V. CONCLUSIONS

Due to the complex indoor channel environment, NLOS propagation and other factors have a great influence on the positioning accuracy, and the positioning accuracy of the traditional positioning algorithm is greatly affected. In this paper, data preprocessing is performed by gross value culling, Gaussian noise filtering and least squares curve fitting, and position estimation by Elman neural network is effective to reduce the positioning error. The experimental results show that the proposed algorithm can overcome the shortcomings of traditional positioning algorithms and can effectively improve indoor positioning accuracy. The positioning accuracy of the indoor positioning system proposed in this paper can be close to 0.3m, and it still has higher positioning accuracy when the positioning node layout is unreasonable.

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