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Research on RFID Indoor Positioning Algorithm Based on GRNN Neural Network

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Abstract: The traditional positioning algorithm based on RSSI (Received Signal Strength Indicator) has some problem such as inaccurate ranging, low positioning accuracy and vulnerability to environmental impact. This is because of occlusion, multipath effect and some other factors in indoor positioning using wireless sensor network technology. To solve this problem, a localization algorithm based on the generalized regression neural network (GRNN) is proposed to avoid the negative effect of the parameter n in the prediction propagation model. The algorithm directly establishes the mapping relationship between the RSSI values received by the reference nodes and their position coordinates in the training stage. In the prediction stage, the RSSI values of the nodes to be located are collected and use the learned GRNN neural network localize the location nodes. The simulation results of MATLAB and RFID show that the location algorithm based on GRNN neural network can provide better location results than the path loss model algorithm and the location algorithm based on BP neural network.

1. Introduction

Radio-Frequency Indentation (RFID) technology is one of the core technologies of the Internet of Things. RFID technology has the characteristics of small size, large data capacity, non-contact identification, etc. Indoor positioning technology base on RFID has always been a research hotspot in the field of Internet of Things. RFID positioning algorithms generally fall into two categories: positioning techniques based on propagation models and positioning techniques based on scene analysis. The location technology based on scene analysis is typically represented by the LANDMARC algorithm, such an algorithm can avoid the interference of the environment to the positioning to a certain extent, but the positioning process requires a large number of reference tags, and the cost is high and the precision is low. The propagation model-based positioning technology mainly includes algorithms based on signal arrival time (AOA), signal arrival angle (TOA), and signal strength based on Received Signal Strength Indication(RSSI). These algorithms measure the signal between the node to be located and the reader. The strength or signal arrival time, angle and other information to achieve positioning, with low cost, high precision, low universal adaptability to indoor complex environment, the current RSSI-based positioning method have been widely studied and used.

The RSSI-based indoor positioning technology is mostly based on the propagation model. After the reader reads the RSSI intensity value of the tag to be located and converts it to the distance of the tag to be located from the card reader, the maximum likelihood method, Taylor series expansion method or Weighted centroid method are used to calculates the coordinates of the tag to be located. In the whole positioning process, the positioning error comes mainly from the process of RSSI conversion to distance. Traditionally, the path loss model is used to transform the location algorithm. However, due to the complexity of the indoor environment, reflection, refraction and multipath effects of signals, the uncertainty of parameter A and path loss index n in the path loss model leads to a large location error based on the path loss model. In order to overcome the shortcomings of the path loss model, a localization algorithm based on BP neural network is proposed. BP neural network is used to fit the relationship curve between RSSI and distance, which enhances the adaptability of parameter A and path loss index n to the environment. However, BP neural network has some defects such as slow convergence speed and is easy to fall into a local minimum.

In this paper, an algorithm based on GRNN neural network is proposed. Compared with BP neural network, GRNN neural network has the advantages of fast learning speed, a better fitting effect of the non-linear model, less sample size and higher noise. The location algorithm based on GRNN neural network utilizes its strong non-linear fitting ability to directly establish the relationship between RSSI and coordinates, thus avoiding the fitting of variable parameters A and N in the path loss model algorithm and the calculation of subsequent location algorithm in the BP neural network location algorithm, which not only reduces the amount of calculation, but also improves the location algorithm for environment universality and positioning accuracy.

2. Traditional Indoor Location Algorithm Based on RFID

2.1 Path Loss Model

In the process of signal propagation in wireless sensor networks, signal intensity changes with distance, and there is a certain relationship between them.

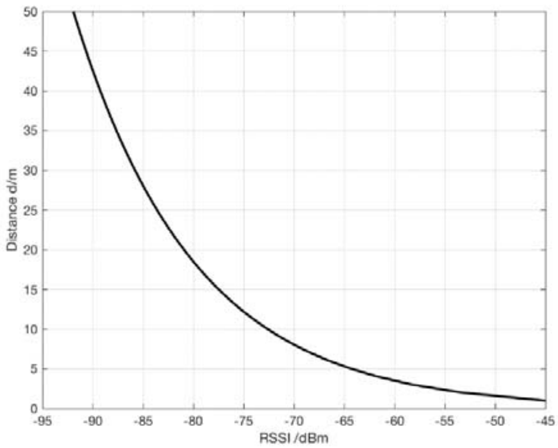

Fig. 1. RSSI-Distance Relationship.

At present, the path loss model used in wireless signal transmission is generally reference Shadowing model.

$$P_r(d) = P_r(d_0) - 10\text{nlog}\frac{d}{d_0} + X$$

Parameters in the formula: d_0 is reference distance from reference node to the card reader, $P_r(d)$ indicates the power received (dBm) when the distance is d meters, X is error term, n is a path loss index related to the environment.

In practice, the average value of d_0 is 1 meter and X is 0. So the path loss model can be simplified to:

$$P_r(d) = P_r(d_0) - 10\text{nlog}\frac{d}{d_0}$$

Let $RSSI = P_r(d)$, $A = P_r(d_0)$.

$$d = 10^{\left(\frac{A-RSSI}{10n}\right)}$$

2.2 The Principle of Maximum Likelihood Estimation

In the positioning area, n card readers read RSSI values of tags to be positioned. According to path loss model or BP algorithm, n distance values with positioning performance to the card reader are obtained as$(d_1 \quad d_2 \quad \cdots \quad d_n)$.

Suppose that n card reader position are $[(x_1 \quad y_1) \quad (x_2 \quad y_2) \quad \cdots \quad (x_n \quad y_n)]$, The coordinates to be positioned is$(x \quad y)$, The following equations can be obtained:

$$\begin{cases} (x_1\text{-}x)^2 + (y_1\text{-}y)^2 = d_1^2 \\ (x_2\text{-}x)^2 + (y_2\text{-}y)^2 = d_2^2 \\ \quad\quad\quad\quad \vdots \\ (x_n\text{-}x)^2 + (y_n\text{-}y)^2 = d_n^2 \end{cases}$$

Conversion equation:

$$\begin{cases} x_1^2\text{-}x_n^2\text{-}2(x_1\text{-}x_n)x + y_1^2\text{-}y_n^2\text{-}2(y_1\text{-}y_n)y = d_1^2\text{-}d_n^2 \\ x_2^2\text{-}x_n^2\text{-}2(x_2\text{-}x_n)x + y_2^2\text{-}y_n^2\text{-}2(y_2\text{-}y_n)y = d_2^2\text{-}d_n^2 \\ \quad\quad\quad\quad \vdots \\ x_{n\text{-}1}^2\text{-}x_n^2\text{-}2(x_{n\text{-}1}\text{-}x_n)x + y_{n\text{-}1}^2\text{-}y_n^2\text{-}2(y_{n\text{-}1}\text{-}y_n)y = d_{n\text{-}1}^2\text{-}d_n^2 \end{cases}$$

In order to facilitate the least squares solution, the equations are represented as $BZ = C$, let $Z = [x \quad y]^T$.

$$B = 2\begin{bmatrix} (x_1\text{-}x_n) & (y_1\text{-}y_n) \\ (x_2\text{-}x_n) & (y_2\text{-}y_n) \\ \vdots & \vdots \\ (x_{n\text{-}1}\text{-}x_n) & (y_{n\text{-}1}\text{-}y_n) \end{bmatrix}$$

$$C = \begin{bmatrix} x_1^2\text{-}x_n^2 + y_1^2\text{-}y_n^2 + d_n^2\text{-}d_1^2 \\ x_2^2\text{-}x_n^2 + y_2^2\text{-}y_n^2 + d_n^2\text{-}d_2^2 \\ \vdots \\ x_{n\text{-}1}^2\text{-}x_n^2 + y_{n\text{-}1}^2\text{-}y_n^2 + d_n^2\text{-}d_{n\text{-}1}^2 \end{bmatrix}$$

Since the matrix B^TB is nonsingular and Z has unique solution, the final solution is obtained:

$$Z = (B^TB)^{\text{-}1}B^TC$$

B and C are known, get the location coordinates is transpose matrix of Z.

2.3 Traditional Rssi Positioning Algorithm & Localization Algorithm Based on Bp Neural Network Error Analysis

In the traditional RSSI positioning algorithm, the path loss index n often uses the empirical value. It is not difficult to find out from the positioning process that the traditional RSSI positioning algorithm error mainly comes from the ranging error. From Equation 3 can know after the RSSI of the node to be located is obtained, parameter A and path loss index n are closely related to distance. In indoor positioning scenarios, due to the reflection and refraction of wireless signals in space, the adaptability of parameter A and n to the environment is very poor, which will directly lead to the inaccuracy of distance. It leads directly to the error and offset of the node to be located.

The core idea of location algorithm based on BP neural network is to use a large number of RSSI and distance value D as training data to train BP neural network, which avoids the defect of selecting path loss parameter n as fixed value in traditional RSSI location algorithm, effectively avoids the influence of environment on location algorithm, and thus improves the location accuracy. However, the shortcomings of the localization algorithm based on BP neural network are obvious:

- The training error of BP neural network is slow convergence, easy to over-fit, dependent on a large number of sample data, and easy to fall into local minimization, which leads to the failure of network training.
- Since BP neural network is used to regress the relationship between RSSI and distance, it still needs to use the maximum likelihood method or Taylor series expansion algorithm to calculate the coordinates of the tags to be located. The number of matrix operations or iterations is too many and the amount of calculation is too large.

3. Localization Algorithm Based on Grnn Neural Network

Compared with BP neural network, GRNN neural network has the advantages of fast learning speed, better fitting of a non-linear model, less sample size and larger noise, and less artificial adjustment parameters, which greatly reduces the impact of subjective assumptions on prediction results. In this paper, the GRNN algorithm is applied to the indoor location scenario based on RSSI.

3.1 GRNN Neural Network Location Model

GRNN consists of four layers: input layer, pattern layer, summation layer and output layer. Corresponding network's input is $X=[x_1 \quad x_2 \quad \cdots \quad x_n]^T$,the output is $Y=[y_1 \quad y_2 \quad \cdots \quad y_k]^T$.In this model, the input is $RSSI=[RSSI_1 \quad RSSI_2 \quad \cdots \quad RSSI_n]^T$,the output is $Y=[x \quad y]^T$.

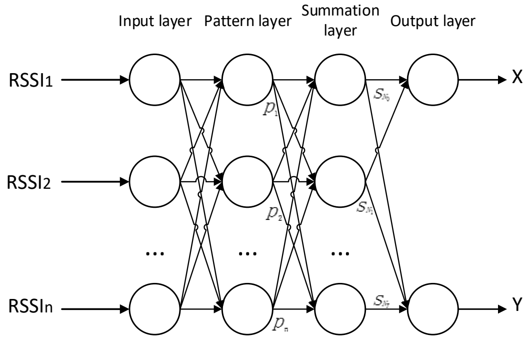

Fig. 2. GRNN neural network model diagram.

The pattern layer's neuron transfer function is:

$$P_i=\exp\left[-\frac{(X-X_i)^T(X-X_i)}{2\sigma^2}\right],i=1,2,\cdots,n$$

$X$is input layer's samples,$X_i$is learning samples corresponding to i th neuron, The smoothing factor is actually the standard deviation of the Gauss function. p_i is i th neuron's output, n is the training sample dimension.

The summation layer's transfer function is:

$$S_{N_j}=\sum_{i=1}^{n} y_{ij}P_i \ ,j=1,2,\cdots,k$$

y_{ij} is the j th element in i th neuron's training output sample. P_i is the i th neuron's output layer, k is the output sample dimension.

The output result is:

$$y_j=\frac{S_{N_j}}{\sum_{i=1}^{n} P_i} \ ,j=1,2,\cdots,k$$

3.2 GRNN Neural Network Location

The experiment was carried out in a 12m*10m room with a positioning area of 9m*7.5m. Card readers were fixed in four corners of the positioning area. A reference label is used to reuse samples. The distribution graph of nodes is shown in Fig 3.

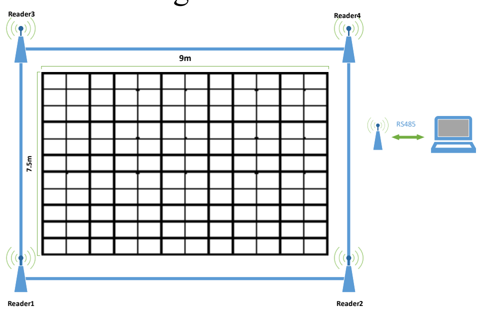

Fig. 3. The layout of experimental nodes.

The positioning process is mainly divided into the following stages:

1) Collection Sample data

The RSSI and coordinate data collected from the experiment are collected from 42 reference labels in the experimental area. The RSSI values of the reference tags and the actual coordinates of the reference tags are read by four card readers respectively as training data. The RSSI values of the reference tags are stored in $[RSSI_1 \quad RSSI_2 \quad RSSI_3 \quad RSSI_4]$ format by four card readers at a time, and are input as training samples. The coordinates of the reference tags are stored in $(x \quad y)$ format as sample output. Each 0.75m mobile data is collected, and 156 sets of test data are obtained.

2) Training GRNN Neural Network

Create a GRNN neural network using newgrnn(Input, Output, spread) function in matlab, where the Input item is the input data set, Output is the expected output value, and spread is the propagation constant. To determine the optimal spread parameters, 75% of the data in the above sample date was used to train the neural network model, and the remaining 25% was used to test the neural network model. Spread is exhaustive between 0.1 and 2 with a step distance of 0.1, using K-fold cross-validation to find the best spread parameters. In the whole process, in order to eliminate the adverse effects of some singular sample data on model training, the input and output data are normalized and denormalized. Finally, the neural network is constructed using the optimal spread parameters obtained. Finally get the best spread value of 1.2.

3) Positioning Moving Tag

Collecting the RSSI of the tag to be located obtained by the card reader as the trained GRNN neural network input, and outputting the coordinate value of the tag to be located.

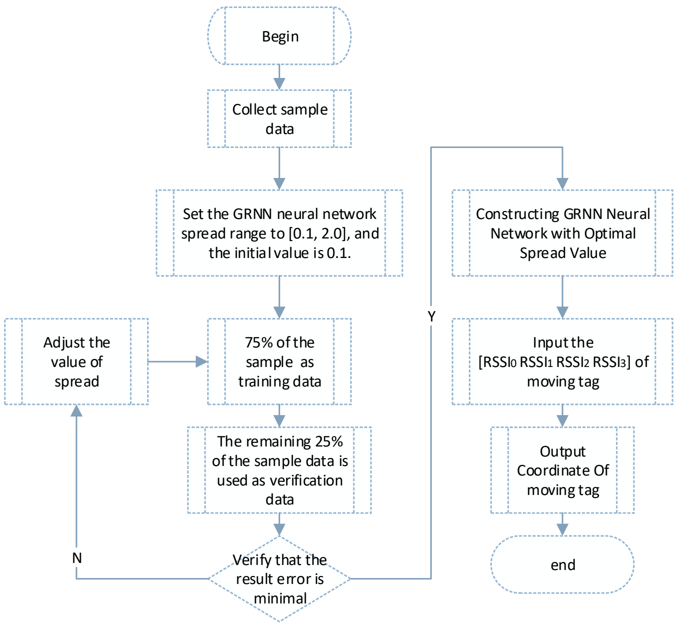

Fig. 4. GRNN neural network location algorithm step diagram.

4. Experimental Results

In the experiment process, in order to compare the positioning effect of the traditional path loss model, BP neural network and GRNN neural network, the data of the tag to be located is collected and simulated in the same indoor environment. The actual coordinates of the tag to be located, the prediction parameters of the traditional path loss model, the prediction coordinates based on the BP neural network localization algorithm and the positioning coordinates based on the GRNN neural network are used to compare the positioning errors of three positioning algorithms. The positioning error is derived from the Euclidean distance between the positioning coordinates and the actual coordinates.

TABLE I. Comparison of three positioning algorithm errors.

Positioning Algorithm	Positioning Error/m		
	Minimum	***Maximum***	***Average***
Path Loss Model	1.14	3.75	2.51
BP Network	0.82	2.78	1.76
GRNN Network	0.72	2.10	1.32

Processed by Matlab.

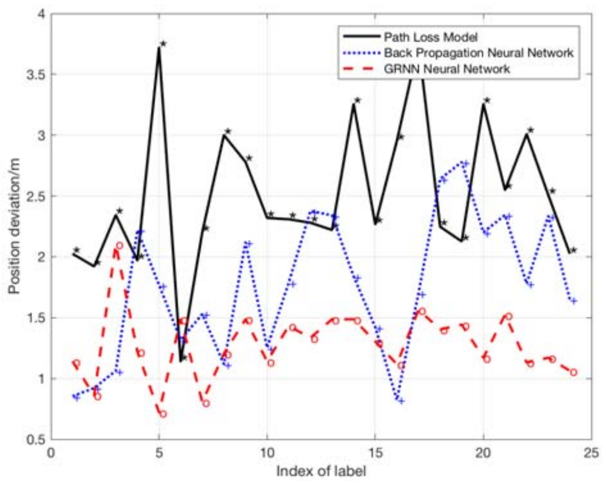

Fig. 5. Positioning error obtained by comparing three kinds of positioning algorithms with actual coordinates.

It is not difficult to analyze the simulation results from TABLE I and Fig 5. Among the three positioning algorithms, the path loss model algorithm has the worst positioning effect, and the BP neural network positioning algorithm is second. The optimal positioning algorithm is the GRNN neural network. Compared with the first two positioning algorithms, the positioning accuracy is improved by 1.2m and 0.5m respectively. It is found by the positioning error that the positioning algorithm based on GRNN neural network can basically ensure that the average positioning error does not exceed 1.4m, and the stability of positioning is better than other two positioning algorithms. The experimental analysis results match the theoretical analysis of the previous papers, indicating that the GRNN neural network-based localization algorithm has the better adaptability to the indoor environment and provides higher-precision positioning results in the same indoor environment.

5. Conclusion

Due to the complexity and change of the indoor environment, the traditional location model based on the path loss model is greatly affected by the uncontrollable factors A and n. The BP neural network based localization algorithm reduces the error caused by the environment to the positioning effect by regression and prediction of the path loss index n. This paper proposes a positioning method based on GRNN neural network, fitting the relationship between learning signal strength and coordinates, directly predicting the coordinates of the tag by signal strength, and reasonably avoiding the influence of parameter A and path loss index n on the positioning result. This paper compares the positioning results of three positioning algorithms in the same indoor environment. The experimental results show that the proposed algorithm effectively reduces the interference of the environment, improves the accuracy of indoor positioning, has a high universality for the indoor environment, and proves the superiority of the algorithm.

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