RFID Indoor Location Based on Optimized Generalized Regression Neural Network

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Abstract. Nowadays, location-based services are common in our daily lives. Traditional Global Positioning System (GPS) location can provide real-time location function in outdoor complex environments, but it is insufficient for indoor location. There are many indoor location technologies, such as ultrasound, Zigbee, RFID and WIFI. RFID location technology has attracted the attention of researchers due to its high precision and low cost. Most existing RFID location algorithms are based on RSSI (Received Signal Strength Indicator) measurement. When converting RSSI to distance, the inaccurate estimation of the path loss parameter may lead to large error. In order to reduce the deviation, this paper proposes a new RFID location algorithm. Specifically, the RSSI of the target tag is read in different directions of the antenna, and the position information is predicted by the general regression neural network, which is optimized by the optimization algorithm. The experimental results show the efficiency of our proposed algorithm.

Keywords: RFID · Generalized regression neural network · Indoor location

1 Introduction

In recent years, the development of the Internet of Things (IoT) has great facilitated our lives. Its device performance has grown rapidly and location-aware applications have proliferated [13]. Location awareness has played an increasingly important role. Providing location information continuously and reliably in both indoor and outdoor environments can provide users with a better user experience. Outdoor location and location-based services have matured, and location-based services based on GPS and maps are widely used and become one of the most used applications for mobile devices. However, due to the interference of building shielding and indoor environment, GPS cannot be used indoors well, such as searching for books in the library and looking for luggage at the airport. Researchers are more focused on how to perform high-precision indoor location.

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In order to meet the needs of indoor object location, the researchers proposed many indoor location technologies [9]. Ultrasonic, sensor, Bluetooth, WIFI and Zigbee technologies are used for location. The author [1] proposed an ultrasound-based indoor location system that calculates the position of the mobile platform by using only ultrasonic signals and the accuracy reaches the centimeter level. The position of the moving target is calculated from the receiver's time difference of arrival (TDOA), and the system has a relatively high cost. In [6], the authors propose a Bayesian inference-based localization algorithm for locating target objects in a 3D WLAN indoor environment, which uses fingerprint technology and the location error is about three meters.

Radio Frequency Identification (RFID) is the crucial technology required to implement the Internet of Thing (IOT), widely used in health detection, smart home, smart city, vehicle location and target tracking, etc. Compare with Sensor, WIFI and Bluetooth, RFID technology has attracted many researchers to deploy applications in indoor positioning environments due to its low cost, high efficiency and low power consumption [3]. There are two types of location algorithm based on Received Signal Strength indicator (RSSI): geometric and fingerprint tags. The geometric method uses the geometric relationship of a circle, sphere or triangle [7] to estimate the position of the target by calculating the distance, as well as the Time of Arrival (TOA) and Angle of Arrival (AOA) [2]. The author [5] proposed an algorithm for RFID location based on hyperbola, which is positioned by limiting the position of the antenna. The reference tag method needs to establish a database of known RFID tag's location information, then to estimate the location of the target tag. In [4, 14], the author proposes a KNN nearest neighbor algorithm to estimate the location information of the test tag, which need a large number of references tags. We hope to design a joint location method to reduce the error of indoor location and not be limited by the location relationship of the antenna.

This paper proposes an indoor location algorithm combining neural network and RFID, without reference tags. After conducting a series of experimental studies, we decided to use three different directions of the antenna to receive the RSSI of the tag, then construct the training data as the input vector of the neural network. The real coordinates of the test tag in the environment is the output vector of the neural network. At the same time, this paper proposes a new optimization algorithm improves the network parameter, and establish the corresponding fitting model to achieve different location in the room.

The main contributions of this paper are summarized as follows:

- We extensively analyze and compare the signal characteristics collected from RFID reader, indicating that RSSI is a stable characteristic of the tag location algorithm proposed in this paper. Not affected by the direction and period of the tag.
- We propose an RFID location method for general regression neural network optimized by mutation particle swarm, called MPSO-GRNN, with regrading to the size of training samples, and the convergence speed of the neural network.

- We design a prototype of MPSO-GRNN using ImpinJ Revolution R420 reader and EPC Gen2 tag. The experimental result shows that the average location error is 0.26 m, and the convergence speed of the optimized GRNN is increased by 61%.

The rest of the structure of this paper is as follows. We will present the background of the second part and conduct an empirical study. The main design of MPSO-GRNN is described in the third part. The fourth section gives the implementation and evaluation. Finally, the fifth section summarizes the paper.

2 Preliminaries

In this section, we will present the background of RFID technology and compare the RSSI and phase signal characteristics using the COTS reader-Impinj Revolution R420 RFID reader and EPC Gen2 tag [12].

2.1 RSSI (Received Signal Strength)

As one of the important characteristic values of RFID signals, RSSI can be received by RFID tags through reading by RFID antenna [8]. The RSSI has an inverse relationship with the distance between the RFID reader's antenna and the RFID tag [16]. The longer the signal propagation distance, the weaker the signal strength. For a better description of the influence of indoor complex environment on signal strength, the path loss signal propagation model is often used as the indoor signal propagation model [11]:

$$RSSI(d) = RSSI(d_0) - 10n \lg \frac{d}{d_0} \tag{1}$$

where n is the path loss factor, d_0 is the known near ground reference distance, d is the distance from the target to the reader and $RSSI(d)$, $RSSI(d_0)$ are the tag signal strengths at distances d and d_0, respectively. When $d_0 = 1\text{m}$, $RSSI(d_0)$ is the average of the received signal strengths at 1 m from the signal transmission location, and the actual applied RSSI ranging formula is obtained:

$$RSSI(d) = RSSI(d_0) - 10n \lg d \tag{2}$$

since each indoor environment is complex, the path loss factor in the equation is not a stable number. This article is mainly used in the location of static tags, we place the tag about 0.45 m in front of the reader antenna, at the same time, we record the RSSI value fed back by the tag, as shown in Fig. 1. When the static tag is within the reader's readable range, the RSSI value is in a small amplitude fluctuation, maintaining between −42 dBm positive and negative.

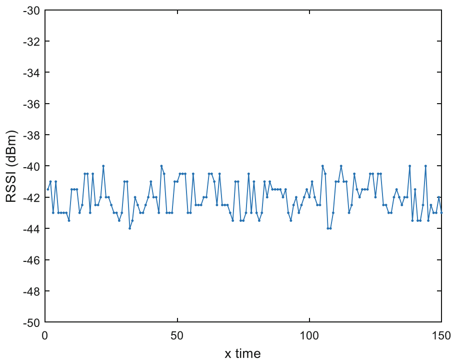


Fig. 1. The RSSI value in an interference environment.

2.2 Phase

Another important feature value of the RFID signal is the phase value, and it can be obtained from the signal fed back from the tag. Again, we place the tag at 0.45 m and record the value of the phase, as shown in Fig. 2. We can find that the phase value will fluctuate greatly and have periodicity. the relationship between RF carrier of frequency f (Hz) and wavelength λ is determined by $\lambda = c/f$, where c indicates that the velocity of the EM wave is equal to the velocity of light ($\approx 3 \times 10^8$ m/s). In addition to the RF phase rotating with distance, the reader's transmission circuit, the reflective characteristics of the tag, and the receiver's receiver circuit introduce some phase rotations called θ_T, θ_{TAG}, and θ_R [10, 15]. Therefore, the total phase rotation is calculated as follows:

$$\theta + 2k\pi = 2\pi \frac{2d}{\lambda} + \theta_T + \theta_{TAG} + \theta_R \tag{3}$$

where θ are the output parameters supported by the generic RFID reader and the number of period is k. Due to the periodicity and sensitivity of the phase, passive tag RFID is difficult to use for large-scale location in phase value characteristics.

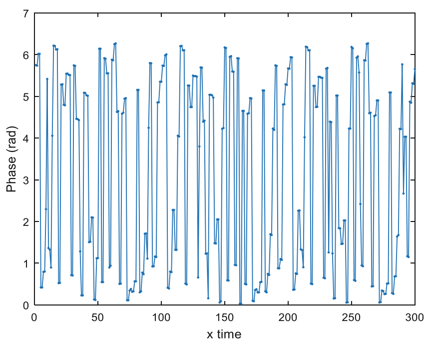


Fig. 2. The phase value in an interference environment.

Therefore, when we decide to use the RFID signals for indoor location, we need overcome the different path loss coefficients and phase cycling characteristics in complex indoor environments. In this paper, we mainly improve the adaptability of multiple environments and the location accuracy. Next, we will use the RSSI eigenvalues and filter to perform data preprocessing. At the same time, we optimize the neural network model to increase the location accuracy of the RFID location and speed up the network convergence.

3 MPSO-GRNN

In this part, we propose an algorithm for generalized regression neural network optimized by mutation particle swarm, called MPOS-GRNN, then gradually introduce our technical details.

3.1 Mean Filter

In order to make the measured value of RSSI approximately equal to the true values, we need to filter out the fluctuation of RSSI values caused by indoor environment or noise interference. Since the target object in this paper is a static tag. We choose the mean filter whose main idea is to average over the domain, the filter formula has the following representation:

$$RSSI_{average} = \frac{1}{n}\sum_{i=1}^{n} RSSI_i \tag{4}$$

where $RSSI_i$ is the i th RSSI value and the size of the sliding window of the filter is n. The average is then calculated, $RSSI_{average}$ is considered the target tag RSSI value.

3.2 GRNN

Generalized Regression Neural Network (GRNN) is a one of the radial basis function network (RBF). But GRNN has more powerful non-linear mapping capabilities and learning speed than RBF, which requires less modeling samples and better prediction results. After determining the number of training samples, the connection weight factor between the corresponding network structure and the neuron can be also determined. The purpose of network training is only to determine its unique parameter smoothing factor σ.

The GRNN structure is shown in Fig. 3. The input layer, mode layer, summation layer and output layer construct the feed forward neural network structure.

The neuron data of the pattern layer comes directly from the input vector of the input layer. Assume the input vector a is n-dimensional $A = [a_1, a_2, \cdots, a_n]^T$, the output layer vector Y is q-dimensional and the number of samples is n. The dimensions of the sample simultaneously determine the number of input layer neurons and the number of pattern layer neurons, and each neuron represents to a different sample.

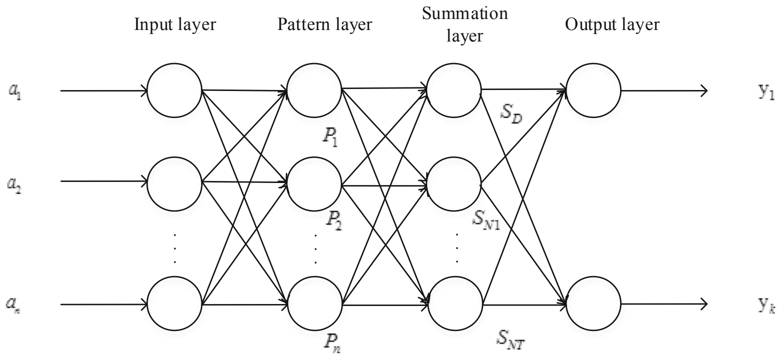


Fig. 3. General regression neural network structure.

The pattern layer is also called the implicit regression layer, and each neuron corresponds to a different learning sample. The number of neurons is the same as the size of training samples, and the neuron transfer function of the pattern layer is:

$$p_i = \exp\left[-\frac{(A - A_i)^T (A - A_i)}{2\sigma_i^2}\right], (i = 1, 2, \ldots, n) \tag{5}$$

Two types of neurons are summed at the summation layer, one of which is calculated as:

$$\sum_{i=1}^{n} \exp\left[-(A - A_i)^T (A - A_i) / 2\sigma_{\mathrm{i}}^2\right] \tag{6}$$

it performs arithmetic sum on the mode layer neuron's output, its mode layer and each neuron have a connection weight of 1, and the transfer function is $S_D = \sum_{i=1}^{n} P_i$. Another calculation method is

$$\sum_{i=1}^{n} Y_i \exp\left[-(A - A_i)^T (A - A_i) / 2\sigma_i^2\right] \tag{7}$$

it weights the pattern layer's neurons, and the weight factor between the i th neuron in the pattern layer and the j th molecule in the summation layer is the first in the i th output sample, the Mapping relations is $S_{Nj} = \sum_{i=1}^{n} y_{ij} P_i (j = 1, 2, \cdots, k)$.

The number of the output layer's neurons is the dimension of the output vector, and the output layer's neurons represents to the j th element of the estimation result $\overline{\mathrm{Y}}(\mathrm{X})$, which is $y_{ij} = S_{Nj}/S_D (j = 1, 2, \cdots, k)$.

3.3 MPSO

The PSO algorithm is derived from the discovery of behavioral characteristics of biological groups and is often used to find the best solution. Each particle in the algorithm represents a possible solution to the issue, and fitness function determines the fitness value of each particle. Particles have direction, distance and speed of motion. Each particle dynamically adjusts its own velocity by comparing it with the motion information of other particles, thereby realizing the optimization of the individual in the solution space.

Suppose $A = (A_1, A_2, \cdots, A_n)$ is the n particles in a M-dimensional search space, the i th particle is represented as a M-dimensional vector $A_i = [a_{i1}, a_{i2}, \cdots, a_{iM}]^T$, which represents the information of the i th particle in the M-dimensional search space and a possible solution to the issue. Then the fitness function can calculate the fitness value of each particle. The velocity of the ith particle is $V_i = [V_{i1}, V_{i2}, \cdots, V_{iM}]^T$, Its individual extremum is $Q_i = [Q_{i1}, Q_{i2}, \cdots, Q_{iM}]^T$, The global extremum of the population is $Q_g = [Q_{g1}, Q_{g2}, \cdots, Q_{gM}]^T$.

Each individual updates its own speed and position with reference to other individual extremum and global extrema during each iteration. The calculation is as follows:

$$V_{im}^{k+1} = \omega V_{im}^{k} + e_1 n_1 (Q_{im}^{k} - A_{im}^{k}) + e_2 n_2 (Q_{gm}^{k} - A_{im}^{k}) \tag{8}$$

$$A_{im}^{k+1} = A_{im}^{k} + V_{im}^{k+1} \tag{9}$$

where ω is the inertia weight, k is the number of iterations, V_{im} is the velocity of the particle, e_1 and e_2 are the acceleration factor and are non-negative, n_1 and n_2 are random numbers from 0 to 1. We find that the particle swarm optimization algorithm is easy to achieve local optimization and low iteration efficiency. Therefore, we use the variation idea in the genetic algorithm to reinitialize the particles with a certain probability after each update of the particles. We call MPSO (Mutation Particle Swarm Algorithm).

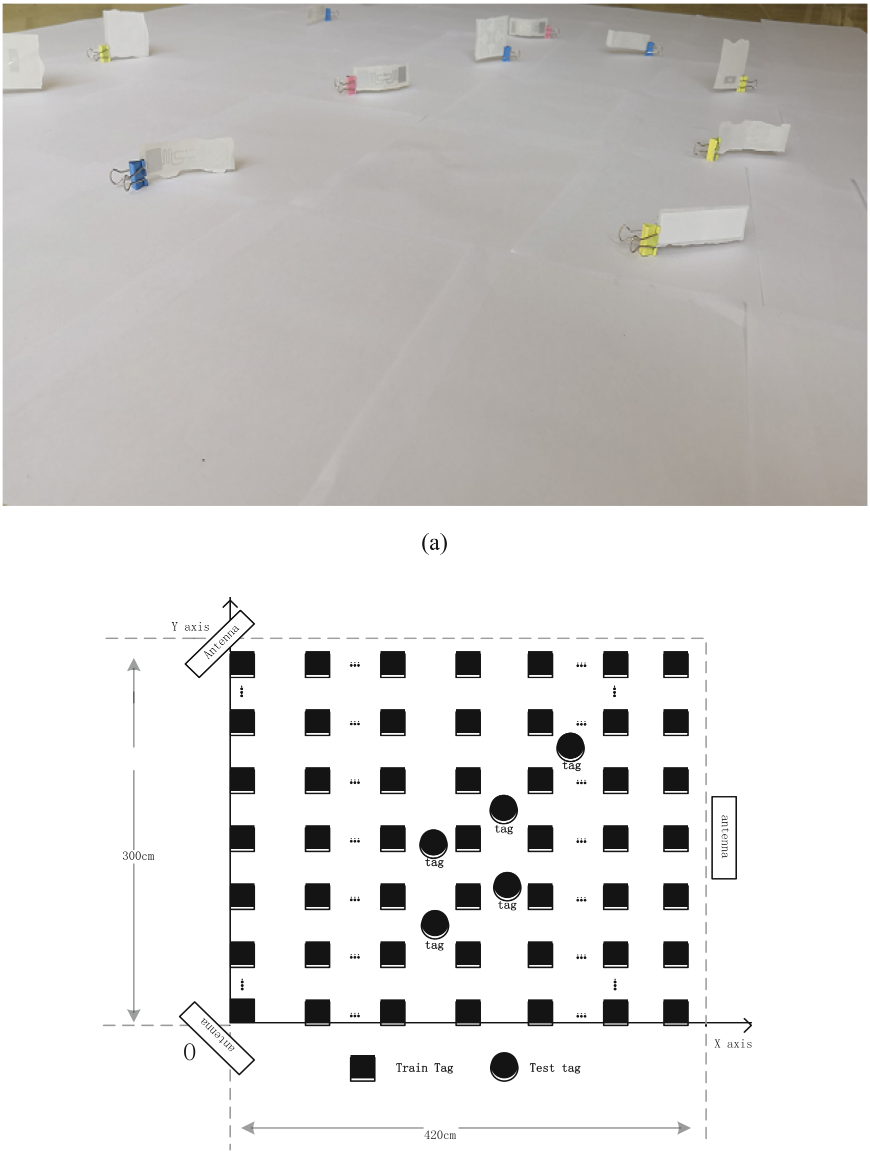
When the GRNN learning sample is established, which also determine the corresponding network structure and the weight coefficient between the neurons. The network training process is to determine the optimal solution of its unique parameter smoothing factor σ. We define the smoothing factor parameter σ of GRNN as the particle of MPSO. Therefore, this paper proposes to use MPSO to optimize GRNN.

According to the characteristics of the tag feedback signal, we set the actual measured RSSI to the input vector of the GRNN network, and the tags are read simultaneously by the antennas in three different directions. Therefore, the dimension of input layer neurons in GRNN is three dimensional, the size of neurons in the pattern layer is the same as the size of neurons in the input layer, and the output layer is defined as the 2D coordinates of the plane in which the tag is located.

4 Implementation and Evaluation

4.1 Experimental Settings

We used the ImpinJ Revolution R420 RFID antenna and the EPC Gen2 tags to lay out the experimental environment, the entire test area is 3.0 m × 4.2 m as shown in Fig. 4a. Since the antenna radiant energy is concentrated within the lobe width, we placed the antenna at 45° in three fixed positions. We place 30 sets of tags to acquire the RSSI values in three directions in the readable area of the RFID reader, then test 10 positions by moving the tags. The detail of position and area of each antenna are shown in Fig. 4b, where the rectangle and the shaded area represent the antenna and the tags, respectively.



(a)

(b)

Fig. 4. Experimental environment. (a) Part of the readable area; (b) Position of each antenna and tag.

4.2 Preprocess for RSSI

We collect the RSSI values of 30 tags by the R420 reader. As shown by the blue curve in the Fig. 5, it shows that the data is unstable. We use the mean filter to handle the RSSI fluctuations. The orange curve in the figure shows the result of the filter processing, and it can be seen that there is stability and there is no large fluctuation.

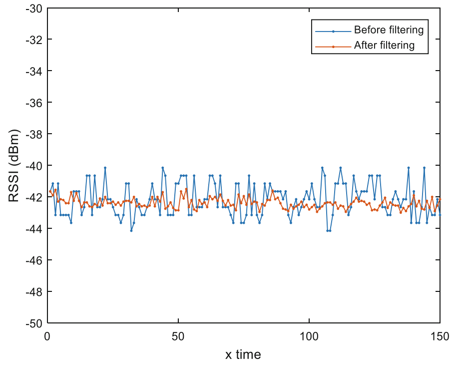


Fig. 5. The RSSI value of tag processed by the filter.

4.3 Average Location Error

First, the RSSI values of 30 sets of static training tags are read from antennas in three different directions of the experimental area. We repeat the process of acquiring the tag data 10 times and input it into the averaging filter with a sliding window of 10. After obtaining the preprocessed data, set the 5/6 of the sample as the input layer training data of the GRNN network, the remaining set is used as the verification set. We consider the network slip factor as the position of the particle, and the MSE of the actual result and the network prediction result is used as the particle fitness. At the same time, the number of particle population and the number of iteration is 50 and 100, respectively. The position of the particle is optimized by the MPSO. On the MATLAB platform, the experimental optimization results are shown in Fig. 6.

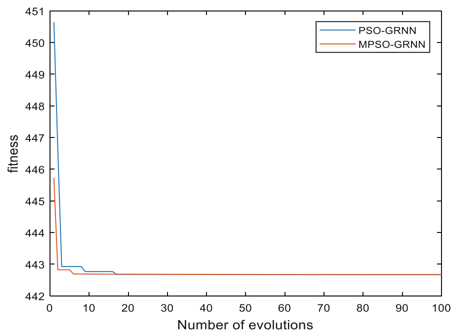


Fig. 6. Optimal fitness particle.

As the figure shows, our proposed optimization algorithm speeds up the convergence and finds the best fitness of particles. It is considered that the position parameter corresponding to the best adaptive particle is used as the optimal sliding factor, and then move the tag to different positions to test the model. At the same time, we will demonstrate the traditional fixed path loss model localization algorithm of RSSI. The results are shown in Figs. 7 and 8:

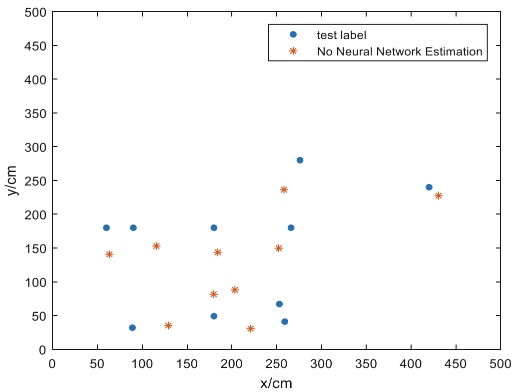


Fig. 7. No neural network localization.

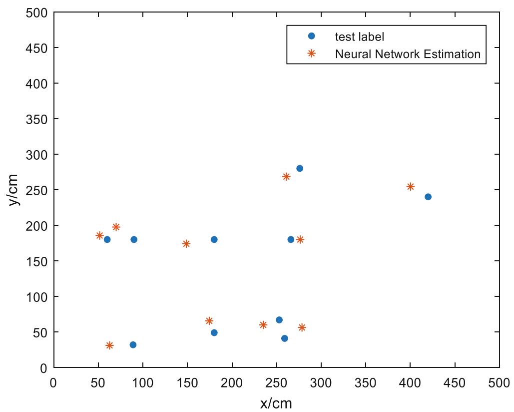


Fig. 8. MPSO-GRNN localization.

As can be seen from the Fig. 9, we also performed 20 repeated tests of different locations for statistical analysis of position error values to obtain the root mean square error curve of the location algorithm.

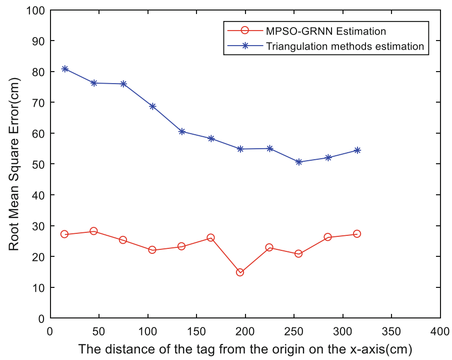


Fig. 9. Root mean square error curve.

The figure shows that the average error of the MPSO-GRNN algorithm is 0.26 m, and the error in the middle of the monitoring area can be reduced to 0.18 m, while the average error of the fixed path loss location algorithm(triangle location algorithm [7]) is 0.49 m, when the tag is located near the coordinate axis (The farthest distance from the antenna), the position error is about 1 m. According to the above analysis results, the traditional path loss location algorithm no well applied to complex indoor environment. This paper proposed the MPSO-GRNN location algorithm reduces the average error and speeds up the convergence. In a way, it overcomes environmental disturbances.

5 Conclusion

This paper proposes an RFID localization algorithm based on generalized regression neural network optimized by mutation particle swarm. This method uses the directional antenna to collect data in different directions in the indoor environment, and finds the optimal particle position information in training model. The more training position information, the higher the test accuracy. The algorithm uses “black box” to correlate the location information with the RSSI value of the tag, thus avoiding the influence of the environmental factor estimation, which improves the location accuracy to a certain extent. It can be applied to complex indoor environments such as factories, laboratories and warehouses.

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