MAC-ILoc: Multiple Antennas Cooperation Based Indoor Localization Using Cylindrical Antenna Arrays

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Abstract. In this paper, a novel RSS (received signal strength) based indoor localization scheme is proposed based on multiple antennas cooperation with designed CAA (cylindrical antenna array). The CAA is composed of twelve directional antennas and could receive the signal of twelve dimensions for one tag at the same time. In the offline phase, the RBF (Radial Basis Function) neural network is trained to construct the relationship between received data of twelve dimensions and AOA (angle of arrival). The online positioning phase consists of two steps. In the first step, the AOA is obtained with the trained neural network and subarea is determined to which the unknown tag belongs. In the second step, the triangle localization algorithm is used in the determined subarea to get the accurate tag position. The experiment results show that the proposed approach not only reduces the miss hit rate for the subarea determination to 6.2%, but also provides comparable location accuracy to that of other two conventional RSS-based locating algorithms.

Keywords: RFID · RBF neural network · Indoor localization
Subarea determination · Directional antenna array

1 Introduction

The RFID (radio frequency identification) technology has attracted continuous attention in both academia and industries in recent years, such as logistics, health care, goods retail for low-cost, noncontact and non-line-of-sight. For example, RFID technology is used as a global localization system for an indoor autonomous vehicle for mobile robot localization and the system provides a really satisfactory performance even in the case that a very small density of tags [1].

Many indoor localization technologies with wireless non-contact radio frequency have been developed, such as indoor positioning based on UWB (ultra wide band), Bluetooth, Wi-Fi and RFID. The UWB [2] takes advantage of TOA (time of arrival) or TDOA (time difference of arrival) algorithm to achieve higher accuracy for the localization. At the same time, this method requires relative expensive hardware to achieve high synchronization accuracy which results into that UWB based indoor positioning technology is difficult to be promoted. The positioning study of Bluetooth and Wi-Fi is becoming more and more widely on account of the popularity of smart

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phones. However, Bluetooth [3] technology can only locate limited number of nodes. The big power consumption has confined promotion of Wi-Fi [4] technology. In comparison with other technologies in large-scale applications, RFID [5] is particularly suitable for indoor localization with the advantage of low power consumption, low price and easy to deploy.

In this study, we have designed the CAA (cylindrical antenna array) in composition of twelve directional antennas. For each tag position, the CAA receives twelve dimensions of tags data and corresponding RSS from twelve directional antennas. The proposed indoor localization method is divided into offline stage and online stage. In the offline stage, the model of RBF neural network is trained with the received information for CAA. In the online stage, the trained model is used to determine the subarea for unknown tags and the triangle localization algorithm are conducted to get the accurate location for unknown tags in the determined subarea.

The rest of the paper is organized as follows. Section 2 describes related work in the field of RSS and neural networks based RSS indoor localization. The overview of the system is given in Sect. 3. The detailed proposed algorithm is presented in Sect. 4. Experiments are conducted about the proposed method in Sect. 5. Conclusion and discussion are given in the final Section.

2 Related Work

In general, there are three kinds of methods for localization based on RSS: the trilateral localization, proximity algorithms and RSS fingerprint-based localization. The trilateral localization [6, 7] bases on the relationship between the RSS and distance. The distance is calculated by the radio signal channel transmission model between the RSS and distance. Then the position of tags is gotten by the trilateral technology with the calculated distances. Proximity algorithms [8] bases on the relative tags preset in the location area. The positioning accuracy is decided by the density of relative tags. RSS fingerprint-based localization [9] bases on the radio map composed of RSS vectors associated with corresponding tags locations.

In practical applications, indoor environment is so complex that it is difficult to be described with the specific equation. With the input of RSS data, the network tunes its inner coefficients to limit to a predefined minimal error. Then, the trained neural network is used to get the location of tags with the obtained RSS from the reader. The artificial neural networks based RSS indoor localization methods are divided into three categories: BPNN (back propagation neural networks) [11–13], FNN (fuzzy neural network) [14, 15] architecture and RBFNN (radial basis function neural network) [16, 17]. Compared with other two methods, the RBF neural network has ability of simple network structure, fast learning, and good approximation ability. So we choose the RBF neural network to construct the complex nonlinear relationship between received data of twelve dimensions and relative angle of arrival.

3 System Overview

The system is constituted by three parts: CAA readers, tags and server terminal. The CAA consists of twelve directional antennas. As shown in Fig. 1, twelve directional antennas are installed at two layers, and each layer includes six antennas. At the each layer, the angle between every two antennas is 120°. The angle between two adjacent antennas is 30° at different layers. Thus twelve antennas are distributed in the direction of 360°, which improves the resolution of angle of arrival. The twelve directional antennas adopt twelve independent radio frequency chips, and transmit to the MCU (micro control unit). The MCU receives and filters the data, and sends the processed data to the server terminal. In order to guarantee the stability of the system, the CAA is mounted in the area where the radius is less than 50 m.

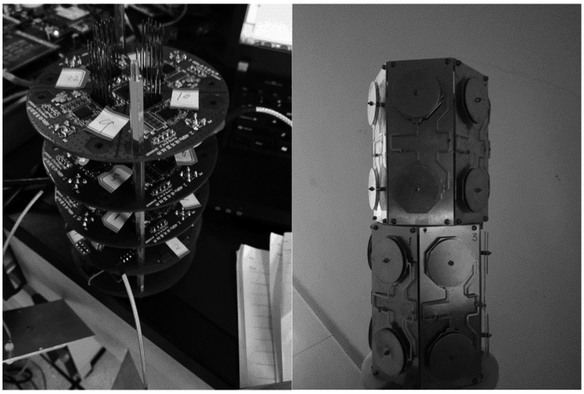

Fig. 1. The hardware of system and CAA.

With the aid of RBF neural network, the paper put forward an AOA based tags localization algorithm using cylindrical antenna arrays readers. The method is implemented in two phases. In the offline phase, RBF neural network is used to map the relationship between angle of arrival and twelve dimensions RSS data from twelve directional antennas. The tags localization is conducted with the two steps in the online phase. The first step is to implement the determination of subarea, and then triangulation positioning algorithm is conducted in the determined subarea.

4 Proposed Algorithm

4.1 Angle of Arrival Calculation

The received signal strength by CAA in the location area is not only determined by the relative angles, but also determined by relative distances between the tag and twelve antennas. Thus the relationship between RSS and AOA is nonlinear and very complicate. The three layers RBF neural network has strong nonlinear fitting ability and can map any complex nonlinear relationship [18]. So in this paper, we introduced the RBF neural network to fit complicate relationship between the twelve dimensions RSS by CAA and the angle of arrival.

RSS Preprocess. The distribution of RSS in the same distance between tag and reader is assumed as Gauss distribution in this paper. In the process of experiment, we find the nature of the signal strength is as following: (1) As the signal strength become weaker, the variance of RSS distribution is bigger. (2) According to the literature [18], the relationship between distance and RSS is logarithmic. When the RSS is lower than −90 dbm, the RSS has no significant change with the increase of distance. It would cause the measurement error increase. For the above two reasons, we limited the received signal strength range to greater than −85 dbm in order to improve the accuracy of positioning. The RSS below −85 dbm would be discarded.

Angle Calculation with RBF Neural Network. In this paper, RBF neural network is used to construct the nonlinear relationship between twelve dimensions RSS and angle of arrival. The three layer RBF neural network has strong nonlinear fitting ability and can map any complex nonlinear relationship.

As shown in Fig. 2, The RBF is composed of three layers: input layer, hidden layer and output layer. The input layer includes twelve nodes and the input vector X is $X = (RSS_{i\_1}, RSS_{i\_2}, RSS_{i\_3}, \ldots, RSS_{i\_10}, RSS_{i\_11}, RSS_{i\_12})$, where RSS_{i_j} refers to the tag signal strength received by j_{th} antenna. The hidden layer nodes include the activation equation and Gaussian radial basis function is used as the activation function in this paper. The output layer contains node A, and the A refers to linear combination of the hidden layer output. The relationship between twelve dimensions RSS and angle α can be described as following equation.

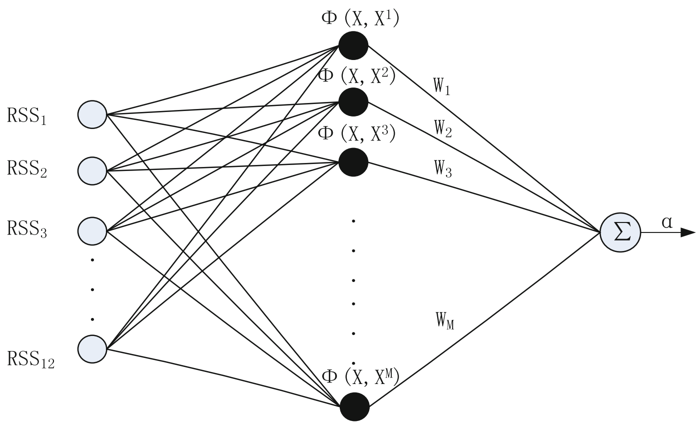

Fig. 2. The structure of RBF neural network.

$$\alpha = \sum_{i=1}^{N} W_i * \varphi_i(RSS_i) \tag{1}$$

where W refers to the output weights, the function φ refers to the activation function in the hidden layer.

Data Set Acquisition. In the offline phase, a series of reference points are set in the location area. Then records are made about the received signal strength and corresponding angle. The format of the collected data X for the j_{th} reference point is (RSS_{j_1}, RSS_{j_2}, RSS_{j_3}, …, RSS_{j_12}, α_j). Then the vector X is taken as the RBF neural network input samples. The relative angle between reference point and reader is taken as the output of neural network.

The Weight Adjustment. In the process of neural network training, the difference between network expected output angle and actual output angle is used as the reference of weight adjustment. The error equation is defined as follows:

$$E = \frac{1}{2} e_q^2 = \sum_{i=1}^{N} \frac{1}{2} (o_i - \hat{o}_i)^2 = \sum_{i=1}^{N} \frac{1}{2} (\alpha_q - \hat{\alpha}_q)^2 \tag{2}$$

where e_q refers to the error when the q_{th} sample is input vector. The $\hat{o}_i$ refers to the network expected output, and the o_i refers to the actual output. The parameter a_q represents the actual angle of arrival and the $\hat{a}_q$ represents the angle derived from the RBF neural network. The parameter N refers to the number of test samples. We adopt LMS (least mean square) to adjust the corresponding weighs in the process of network training, as shown in Eq. 3.

$$\Delta W_i = \delta(o_q - W_q^T * \Phi) * \Phi \tag{3}$$

where δ is learning rate for the neural network. We constantly input training samples into the network, and adjust the weight to make the actual output of the network tend to expect output, until the training error reduced to an acceptable range. We used a set of 2000 original data as the input of training model and used a set of 200 data as the test data for the trained model.

AOA Acquisition. In the online phase, the reader received twelve dimensions RSS in the same time for a fixed time interval. The collected RSS will be averaged in the same dimensions and put into the trained ANN model to get the corresponding angle.

4.2 Subarea Determination

Due to multipath and NLOS (non-line of sight) interference in the indoor environment, the traditional RSS-based subarea determination caused a big bias and the hit rate for the right subarea is less than 85% [20]. Most of RF signals transmission is by the door or window and the rooms are not always separated by concrete, which would cause error by using the method of attenuation. Jiang [19] conducted the subarea determination with RSS order. The RSS is stronger in the subarea than the area out of the subarea. However, the assumption is invalid in the complex environment, which would cause the localization error.

Based on the calculated angle of arrival for the tags, the paper put forward a subareas determination method. As shown in figure, we deployed three CAA readers in the corner of the subarea. In order to eliminate the noise of the RSS, we use the redundancy design are designed and we use three readers instead of two readers to implement the subarea determination. If the AOA of tag calculated by three readers satisfies the conditions $\{3\pi/2 > \alpha_1 < 2\pi, 0 < \alpha_2 < \pi/2$ and $\pi/2 > \alpha_3 < \pi\}$, it is thought that tag is in corresponding subarea (Fig. 3).

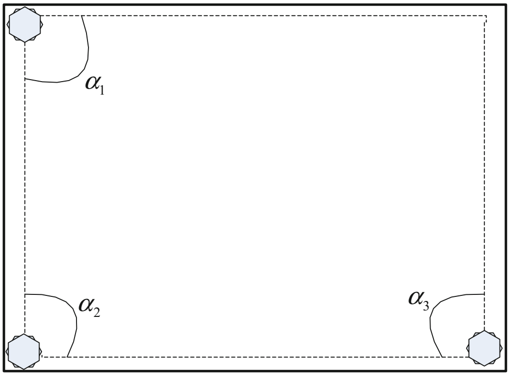

Fig. 3. The subarea determination graph

4.3 Tag Localization in Subarea

After the determination of subarea, the AOA based triangle positioning algorithm is conducted to get the location of unknown tags. As shown in Fig. 4, three CAA readers are prearranged in a subarea. However, if the relative angle of arrival equals zero, it is impossible for the two readers to get the tags position. The unknown tag position can be obtained with the Eq. 4.

$$\begin{cases} b^2 = a^2 + c^2 - 2ac\cos\alpha \\ a^2 = b^2 + c^2 - 2bc\cos\beta \end{cases} \tag{4}$$

where α, β refers to relative angles of arrival, the parameter a, b, c refers to the sides of the triangle. The triangle sides can be expressed as Eq. 5.

$$\begin{cases} a^2 = (x_1 - x_{12})^2 + (y_1 - y_{12})^2 \\ b^2 = (x_2 - x_{12})^2 + (y_2 - y_{12})^2 \\ c^2 = (x_1 - x_2)^2 + (y_1 - y_2)^2 \end{cases} \tag{5}$$

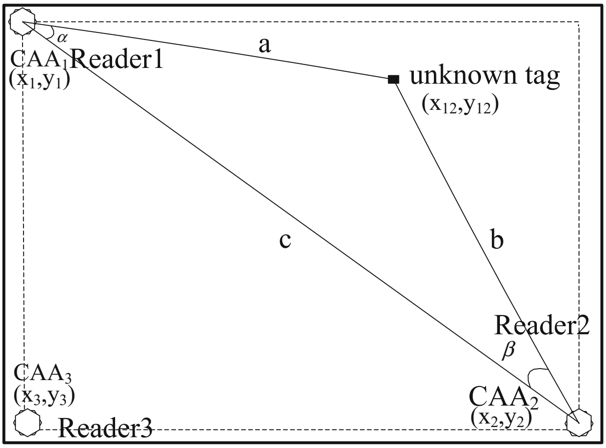

Fig. 4. Tag localization in determined subarea

The corresponding coordinates (x_{12}, y_{12}) can be calculated with the above equation. For three readers, three groups of coordinates for unknown tag can be derived. With the reader 2 and reader 3, we can get the coordinates (x_{23}, y_{23}). With the reader 1 and reader 3, we can get the coordinates (x_{13}, y_{13}). Then the location of the tag is derived in Eq. 6.

$$\begin{cases} x = \dfrac{x_{12} + x_{13} + x_{23}}{3} \\ y = \dfrac{y_{12} + y_{13} + y_{23}}{3} \end{cases} \tag{6}$$

where the parameter N refers to effective calculated coordinates. If the value of relative angle is zero, the calculated coordinates is thought to be ineffective.

5 Experiments

We conducted three experiments with the following designed system. The NRF52832 from Nordic company is adopted as MCU of 2.4 GHz RFID reader. The NRF24LE1 from Nordic company is adopted as MCU of RFID tags. The maximum send power of RFID tag is 4 dbm. The size of the directional antenna is 10 cm × 4 cm rectangular antenna. As shown in Fig. 1, twelve directional antennas are integrated into the CAA. In CAA, the main control chip is STM32F407. The server terminal configuration is Quad - Core Intel Core i5 and 8 GB RAM. The experiments were conducted in the area as shown in Fig. 5. The black lines and arrows show the walk paths and directions of tester. The black dots refer to place where received signal strengths are collected.

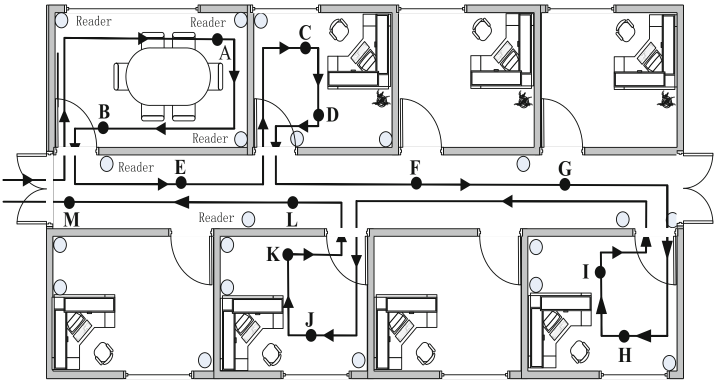

Fig. 5. The deployment of cylindrical antenna array and the system.

5.1 Subarea Determination Comparison

To verify the effectiveness of subarea determination method, we compared proposed method with other two kinds of relevant methods. In the first method, the fingerprint is used to determine the subarea. In the second method, we used the order of RSS in the paper [19] to conduct the subarea determination. We conducted experiments with three methods to determine the subarea in the same scenario. As is shown in Fig. 5, the path we walked is expressed as arrowed line. The RSS information was collected on the nine points (from the position A to the position I). We had conducted the experiments with three methods for five rounds and calculated the hit rates for the right subarea for these points. As it is shown in the Table 1, the proposed method provides highest hit rate for the subarea determination among three methods.

Table 1. The comparison of three different subarea determination methods

Methods	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	Hit rates
Fingerprint based method	10	10	12	11	12	84.60%
RSS order based method	11	13	10	12	12	89.20%
Proposed method	13	11	12	12	13	93.80%

5.2 The Comparison of Three Different Localization Methods

In order to verify the effectiveness of the proposed localization method, we compared three methods: proposed method, the fingerprint-based method [21] and trilateral positioning method [10]. The three methods were conducted in the same subarea and used three readers in the same position. The CDF of three methods is depicted in Fig. 6. As it is shown in the figure, the accuracy of trilateral positioning method is lowest, and the positioning accuracy of proposed method is highest in three methods.

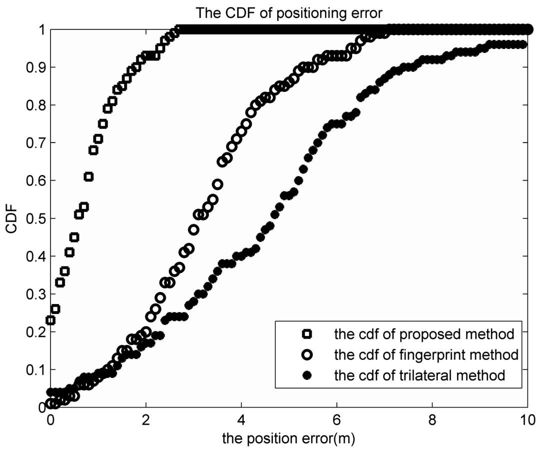

Fig. 6. The CDF of positioning error for three different methods.

6 Conclusion

The paper designed cylindrical antenna arrays and implemented AOA based indoor positioning system. The proposed method employs the RBF neural network to model the complex nonlinear relations between twelve dimensions RSS and corresponding AOA. Based on the calculated angle, we used the two steps solution to conduct the indoor localization. In the first step, a subarea is determined to which the unknown tag belongs. In the second step, the triangle localization algorithm is used in the determined subarea to get the accurate tag position. Through the experiment, it is proved that the proposed methods can improve the location accuracy with the help of CAA. In this paper, we conduct the proposed paper in the LOS condition. In the future research, the work will be focused on the use of CAA in the complex indoor environment.

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