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A Fuzzy C-Means and Hierarchical Voting Based RSSI Quantify Localization Method for Wireless Sensor Network

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ABSTRACT In recent years, wireless sensor networks (WSN) have been widely used in many areas due to the rapid development of wireless communication and microelectronics. The positioning of mobile nodes is one of the key applications of WSN. In this paper, we propose a received signal strength indicator (RSSI)-based positioning scheme. We use the Fuzzy C-Means (FCM) algorithm to provide a practical quantized threshold designer for RSSI data, which is used to convert quantized data based on received signal strength into the distance. Then, we propose a hierarchical voting-based positioning scheme for calculating the position of the mobile node. The proposed algorithm can weaken the influence of non-line of sight (NLOS) error on the positioning result. And the simulation results show that it has better performance than particle swarm optimization (PSO) and quantized distributed gradient target localization using quantized received signal strength (QDG-QRSS) in most cases. The actual experimental results show that the proposed algorithm can also get higher localization accuracy in the indoor environment, and it is robust to the NLOS errors.

INDEX TERMS Wireless sensor network, non-line of sight, mobile localization, received signal strength indicator, fuzzy logic method.

I. INTRODUCTION

Wireless sensor network (WSN) is a network of hundreds of low-cost, low-power, and densely distributed sensors. These sensors typically only have very limited resources, such as sensing and communication bandwidth, while collecting information about specific events of interest and sent the information to a fusion center (FC) [1] for further processing. With major advances in wireless communications and microprocessors, the topic of WSN has become a rapidly evolving research area with great potential for commercial, military and security applications, such as environmental monitoring (fires, floods) [2], shape detection (urban terrain, healthcare) [3], target location [4] and target tracking [5].

WSN-based indoor positioning [6] is imperative for accurate tracking of indoor targets and higher-level motion analysis, it has become a hot research topic in recent years. A node having known coordinate information is referred to as a beacon node, and a node having no coordinate information is defined as a mobile node. In the WSN-based positioning method, beacon nodes are randomly deployed in a region of interest (ROI). The beacon node measures the distance or angle from the mobile node, and then sends the data to the FC. The FC collects these measurements and fuses them in order to calculate the location of the mobile node. In recent years, researchers have proposed several positioning methods [7]–[11]. The main measurement methods are angle of arrival (AOA) [7], direction of arrival (DOA) [8], time of arrival (TOA) [9], time difference of arrival (TDOA) [10] or received signal strength indicator (RSSI) [11]. In WSN, although RSSI measurements are typically used for target detection, they can be used for positioning without any additional sensor functions. Therefore, we mainly investigate the RSSI-based localization method in this paper.

However, the line of sight (LOS) between the mobile node and the beacon nodes is not always guaranteed, when the radio waves are scattered to reflect or penetrate the blocking object [12]. It will cause the signal propagation time

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to increase, which is named as the non-line of sight (NLOS) problem [13]. In this paper, we show that by adopting a specific fuzzification and positioning scheme, the degradation of positioning performance caused by non-ideal communication channels can be significantly improved.

In this paper, we propose a method named as Fuzzy C-Means and Hierarchical Voting methods RSSI and Quantify Localization (FHRQ) to quantify RSSI measurements and mitigating NLOS errors for 2D scenes. We first use the fuzzy c-means (FCM) algorithm to provide a set of quantization thresholds for RSSI-based measurements based on the wireless propagation model in the LOS case. Then, the hierarchical voting method is used to directly estimate the location of the mobile node. The proposed method mainly has the following advantages:

(1) The FCM algorithm is used to calculate the quantization threshold. This method only needs the signal propagation parameters under the LOS condition, and does not need any a priori information about the NLOS error, and is robust to the NLOS error.

(2) The proposed hierarchical voting based positioning algorithm has a stabilizing effect. The proposed algorithm can still maintain good results after various parameters of the system change.

(3) When the NLOS error obeys different distributions, by observing the simulation results of the proposed algorithm, we find that it can effectively reduce the influence of NLOS error on the positioning results and always has a good performance.

(4) The experimental results show that in the actual environment, the proposed method still maintains good results and is robust.

The structure of this paper is as follows: In section 2, we present the progress of research on positioning based on quantitative data and positioning in the case of NLOS. In section 3, the measurement model we use to measure RSSI and a brief introduction to FCM are introduced. In section 4, we describe the algorithm we proposed in detail. The results of the simulation and actual experiments are shown in section 5. And we describe the conclusion in section 6.

II. RELATED WORKS

In recent years, the positioning based on quantitative data [14]–[21] has caused a lot of attention. In [14], in addition to the RSSI-based maximum likelihood (ML) target position estimator using quantized data, an optimization design method for quantization thresholds and two heuristic design methods are proposed. In [15], based on the local voting decision fusion (LVDF) mechanism, a new algorithm is proposed, which uses the data of adjacent sensors to correct the original decision first, and then uses the pseudo-likelihood formula and EM algorithm to locate, especially suitable for low signal to noise ratio environments. In [16], they studied the relationship between quantization level and network configuration parameters and the lower bound of the positioning error based on the quantized RSSI, and further discussed the influence of network configuration on positioning accuracy. In [17], a deterministic annealing method is proposed for the design of effective quantizers for distributed source coding systems, which is used to design all components of a general robust distributed source coding system. By independent of initialization, and without making any simplifying assumptions about the underlying source distribution, many undesirable local optima are avoided and good results are obtained. In [18], different wireless channel models and receiver architecture ML targets are derived by incorporating the statistics of imperfect wireless channels between the sensor and the FC and some physical layer design parameters into the positioning algorithm. The position estimator forms a new maximum likelihood (ML) target location method, which can also achieve good results when the number of sensors is small. In [19], based on the available data for each iteration, the approximate a posteriori pdf of the source location is used to compress the quantized data of each activated sensor using distributed data compression techniques, and based on the mutual information and the posterior Cramér-Rao lower bound (PCRLB) performs the selection of iterative sensors, thereby significantly reducing communication requirements. In [20], by introducing a new structure and practical framework, the channel coding principle is incorporated into the source coding problem, and the problem of distributed source coding is solved on this basis. In [21], it is demonstrated that the correlation between sources can be used to reduce quantization distortion and protect data when transmitted over non-ideal channels. In [22], a quantized distributed gradient target localization using quantized received signal strength (QDG-QRSS) method is proposed, which uses QRSSI measurements for target location in WSN. In the QDG-QRSS algorithm, firstly, combine the PSO with their proposed formula to generate a fixed set of thresholds, and then use it to quantize the measured RSSI data. Based on the obtained QRSSI data, PSO and optimized QDG algorithm are used for accurate and efficient positioning.

At the same time, there are many researches on positioning algorithms for complex NLOS situations. In [23], they proposed a state space system framework based on Markov-transitioned multiple models to verify the measured values and form an improved selective fuzzy-tuned IMM-EKF (SFT-IMM-EKF) method. In [24], the TOA and RSSI measurement methods are adopted, and they approximate nonlinear RSSI with multiple linear equations using fuzzy techniques. At the same time, the IMM is used to switch the LOS and NLOS states, effectively reducing the influence of NLOS on the measurement error. In [25], the positioning problem is transformed into a generalized trust region sub-problem (GTRS) framework, which reduces the derived estimator over a readily obtained interval, and then uses the bisection procedure to solve it accurately. In [26], based on the RSSI measurement of the WiFi signal, two machine learning-based algorithms are proposed to obtain several statistical features of the RSSI time series, and then the hypothesis-based algorithm is used to identify the NLOS measurement. Our previous paper [27] can only be based on the measured distance. This paper can directly use the RSSI measurement. At the same time, compared with the previous papers, the proposed algorithm simplifies the computational complexity and optimizes the hierarchical voting-based localization algorithm.

III. BACKGROUND

A. MEASUREMENT MODEL

First, we consider a wireless sensor network, assuming that N beacon nodes ($\mathbf{c}_i = [x_i, y_i]^{\mathrm{T}}, i = 1, \ldots, N$) are randomly deployed in the $M \times M$ field, where M indicates the scope of the experimental environment. The location of the obstacles is unknown. The mobile node moves randomly in the field, at time k the position of mobile node is $\mathbf{u}_k = [x_k, y_k]^{\mathrm{T}}, k = 1, \ldots, K$. This paper considers a 2-D localization scenario.

The beacon node sends a signal; the mobile node receives the signal and converts it into distance information. The positioning method based on the received signal strength indication (RSSI) mainly uses the energy loss of the electric wave during propagation to calculate the distance. The mobile node transmits a radio wave with a specific signal strength, and the receiving node converts the energy loss during transmission into a distance between the nodes according to the signal strength of the received electric wave, and further determines the position of the mobile node. At present, there are three types of wireless propagation model commonly used in WSN: free-space model, two-ray ground reflection model, and shadowing model. Since the shadow model fully considers the change of environmental factors, and can easily use the path attenuation factor α and the shadow n_i to conveniently adjust the effect of the whole model, so that the curve can be quickly fitted in the actual measurement. So we chose the shadowing model [28], then the received signal strength by the beacon node is:

$$P\left(d_k^i\right) = P(d_0) - 10 \cdot \alpha \cdot \log_{10} \frac{d_k^i}{d_0} + n_i \tag{1}$$

where $d_k^i = \|\mathbf{u}_k - \mathbf{c}_i\|$ is the distance between $\mathbf{u}_k$ and $\mathbf{c}_i$, $P\left(d_k^i\right)$ indicates the received signal strength measured at the distance d_k^i. α is the path loss exponent which varies between 1 and 3 under LOS condition or 3 and 6 under NLOS condition. n_i represents the log-normal shadowing noise modeled as a Gaussian variable with the mean μ and standard derivation σ, $n_i \sim N\left(\mu_{LOS}, \sigma_{LOS}^2\right)$ under LOS condition and $n_i \sim N\left(\mu_{NLOS}, \sigma_{NLOS}^2\right)$ under NLOS condition, with $\mu_{LOS} < \mu_{NLOS}$ and $\sigma_{LOS}^2 < \sigma_{NLOS}^2$. And d_0 is a reference distance, we assume $d_0 = 1$ in the following derivations.

B. A BRIEF INTRODUCTION TO FUZZY LOGIC METHOD

Fuzzy logic refers to a control technique that selectively executes an instruction in a fuzzy region between two values that are allowed to be defined. Because it simulates the human mindset, it is more suitable for people to observe, think, understand and make decisions. It can achieve good results for all kinds of multivariable complex systems with nonlinear, strong coupling, uncertainty and time-varying. In the node localization technology for WSN, due to the nonlinear and uncertain problems in the process of distance measurement between nodes, fuzzy control can be used as a new control strategy to express the expert knowledge of specific fields, and make correct decisions on the real-time state of the system through fuzzy reasoning. This eliminates the need to use accurate mathematical models of the system and is robust and adaptable to changes in the parameters of the system.

In our fuzzy logic controller, we chose the FCM algorithm for fuzzification. The FCM algorithm is a partition-based clustering algorithm. Its idea is to make the similarity between objects divided into the same cluster the largest, and the similarity between different clusters is the smallest. It is an improvement of the ordinary C-means algorithm, introduces the concept of membership degree, and improves its application range, and is the earliest proposed fuzzy segmentation algorithm. The ordinary C-means algorithm is hard to divide the data, while FCM is a kind of flexible fuzzy division.

IV. PROPOSED METHOD

As shown in Figure 1, the input of the method is the received signal strength P_k^i and the output of the method is estimated position of mobile node$\left[\hat{x}_k, \hat{y}_k\right]^{\mathrm{T}}$, and we can divide the proposed algorithm into three parts:

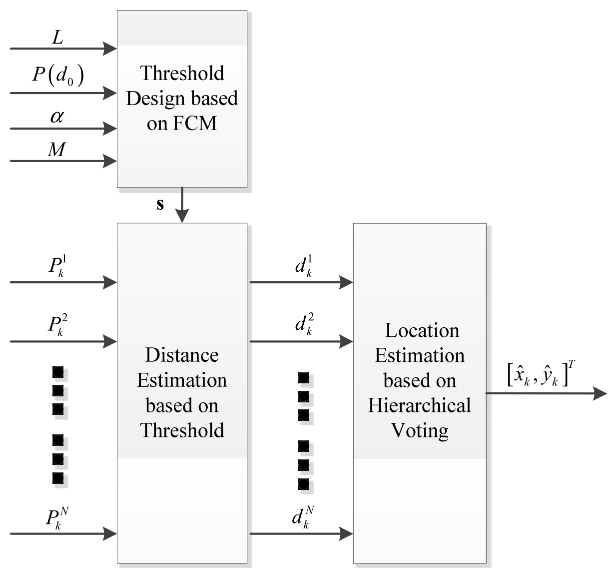

FIGURE 1. The flowchart for the proposed algorithm.

Threshold Design Based on FCM:

In the initial stage we first use the FCM to determine a set of quantization thresholds s for RSSI measurements. As the NLOS error will affect the measured value, after the fuzzification, the influence of the NLOS error on the positioning effect can be weakened.

Distance Estimation Based on Threshold:

Then we can use it to convert the RSSI measurements P_k^i into the distance d_k^i.

Location Estimation based on Hierarchical Voting:

After obtaining the distance d_k^i, the final estimated position $\left[\hat{x}_k, \hat{y}_k\right]^{\mathrm{T}}$ can be obtained by using the hierarchical voting algorithm. In the process of hierarchical voting, as the mean and variance of the noise in the LOS case are considered, the interference of the noise on the signal is reduced. And the influence of the single NLOS error on the final positioning result is reduced, so that the positioning accuracy is effectively improved.

A. GENERAL CONCEPT

Let $i-th$ node obtain the RSSI measured value at time k asP_k^i. Without loss of generality, we assume that the mobile and beacon nodes are placed in a 2-dimensional space. Let $\mathbf{u}_k = [x_k, y_k]^{\mathrm{T}}$ denote the coordinate of the mobile node and $\mathbf{c}_i = [x_i, y_i]^{\mathrm{T}}$ denote the coordinate of beacon node i where $i = 1, \ldots, N$. Then the received signal strength P_k^i (in dBm) from the mobile node to beacon node i under log-normal shadowing conforms to the Equation (1), can be modeled as:

$$P_k^i = P\left(d_k^i\right) \tag{2}$$

B. THRESHOLD DESIGN BASED ON FCM

Before converting the RSSI measurements into distance, we should firstly blur the measurements. We choose FCM to determine a set of quantization thresholds $\mathbf{s}$, and use them to estimate the measured distance from the node.

First we define in this model that ν_i is $i-th$ cluster center, x_j is the $j-th$ data point, μ_{ij} is the degree of membership of x_j belongs to the cluster center ν_i. And it satisfies the following properties:

$$\sum_{i=1}^{L} \mu_{ij} = 1, \forall j = 1, \ldots, n \tag{3}$$

Based on the membership degree, we can regard the FCM algorithm as a simple iterative process:

***Step*1:** We initialize the membership matrix μ_{ij} with random numbers between 0 and 1 and satisfy the constraints in equation (3).

***Step*2:** Then we can calculate L cluster centers:

$$\nu_i = \frac{\sum_{j=1}^{n} \mu_{ij}^m x_j}{\sum_{j=1}^{n} \mu_{ij}^m} \tag{4}$$

where m represents the weight exponent of membership degree, and we set $m = 2$ in this paper.

***Step*3:** So we can get the value function as:

$$F = \sum_{i=1}^{L} \sum_{j=1}^{n} \mu_{ij}^m d_{ij}^2 \tag{5}$$

where $d_{ij} = \left|\nu_i - x_j\right|$ represents the Euclidean distance between the $i-th$ cluster center and the $j-th$ data point

If it is less than a certain threshold, or if its change from the last value functions value is less than a certain threshold, the algorithm stops.

***Step*4:** Update the membership degree as follow:

$$\mu_{ij} = \left(\sum_{k=1}^{L} \left(\frac{d_{ij}}{d_{kj}}\right)^{\frac{2}{m-1}}\right)^{-1} \tag{6}$$

Then return to the step two.

After obtaining the clustering center, we use the change of the membership degree corresponding to each cluster center to find the boundary points between each two cluster centers. The final result is the designed threshold.

We can summarize the threshold design based on FCM as the following pseudo code shown in Algorithm 1. In Algorithm 1, we define some new parameters to store some temporary variables, where $P(d_0)$ indicates the received signal strength measured at the distance d_0, $\mathbf{temp}_{dis}$ represents the distance corresponding to the sample used for clustering, $\mathbf{temp}_{rss}$ represents the RSSI measurement value for clustering, **CENTER** represents the clustering center of the algorithm output, **U** represents the membership matrix of each point relative to the cluster center. **INDEX** is a collection of index vectors for any of the previous data in **CENTER**. *find_s* represents the number of the threshold currently being searched.

Algorithm 1 Threshold Design Based on FCM

Input: $L, P(d_0), \alpha, M$
Output: $\mathbf{s}, \mathbf{D}$
begin
$\mathbf{temp}_{dis} = 0 : 0.1 : \sqrt{2} \cdot M$
$\mathbf{temp}_{rss} = P(d_0) - 10 \cdot \alpha \cdot \log_{10}\left(\mathbf{temp}_{dis} + 1\right)$
$[\mathbf{CENTER}, \mathbf{U}] = fcm\left(\mathbf{temp}_{rss}, L\right)$
$[\sim, \mathbf{INDEX}] = sort(\mathbf{CENTER})$
$\mathbf{s}(0) = P(d_0)$
$find\_s = 1$
for $i = 1 : length(\mathbf{U})$
if $\mathbf{U}(\mathbf{INDEX}(find\_s), i) < \mathbf{U}(\mathbf{INDEX}(find\_s + 1), i)$
$\mathbf{s}(find\_s) = \mathbf{temp}_{rss}(i)$
if $find\_s < L - 1$
$find\_s = find\_s + 1$
else
break
end if
end if
end for
$\mathbf{s}(L) = P(d_0) - 10 \cdot \alpha \cdot \log_{10}\left(\sqrt{2} \cdot M + 1\right)$
End

C. DISTANCE ESTIMATION BASED ON THRESHOLD

Using the RSSI measurement model and the quantization thresholds $\mathbf{s}$, the raw RSSI measurements are quantized into discrete data K_i:

$$K_i = \begin{cases} 0 & if\ \mathbf{s}(0) < P_k^i < \mathbf{s}(1) \\ 1 & if\ \mathbf{s}(1) < P_k^i < \mathbf{s}(2) \\ \vdots & \vdots \\ L-1 & if\ \mathbf{s}(L-1) < P_k^i < \mathbf{s}(L) \end{cases} \tag{7}$$

We assume that $\mathbf{D}$ represents the membership degree of the RSSI measurement for each quantization threshold, and the shape of the fuzzy membership function curve is triangle. When the number of cluster centers L is equal to 2, it roughly obeys such a distribution as shown in Figure 2:

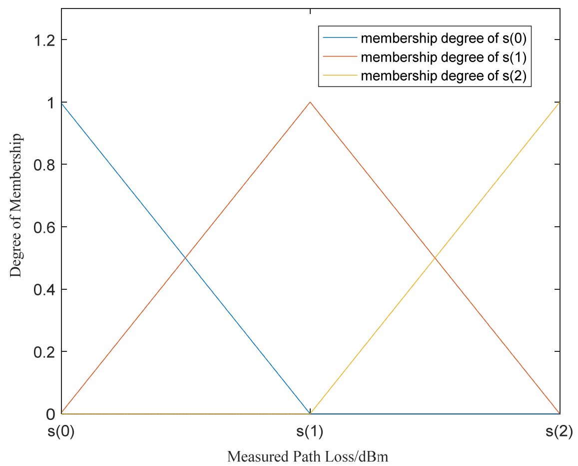

FIGURE 2. Function of Membership Degree.

In Figure 2, $\mathbf{s}$ represents a set of quantization thresholds calculated by FCM.

Then we can get the membership degree $\mathbf{D}(K_i)$ and $\mathbf{D}(K_i+1)$ to the two nearby thresholds of the measured value P_k^i is $\frac{\mathbf{s}(K_i+1)-P_k^i}{\mathbf{s}(K_i+1)-\mathbf{s}(K_i)}$ and $\frac{P_k^i-\mathbf{s}(K_i)}{\mathbf{s}(K_i+1)-\mathbf{s}(K_i)}$, respectively. Then the final estimated distance d_k^i can be obtained as $d_k^i = \mathbf{D}(K_i) \cdot \frac{\mathbf{s}(K_i+1)-P_k^i}{\mathbf{s}(K_i+1)-\mathbf{s}(K_i)} + \mathbf{D}(K_i+1) \cdot \frac{P_k^i-\mathbf{s}(K_i)}{\mathbf{s}(K_i+1)-\mathbf{s}(K_i)}$.

We can summarize the distance estimation based on threshold as the following pseudo code shown in Algorithm 2.

Algorithm 2 Distance Estimation Based on Threshold

Input: $\mathbf{s}$, $\mathbf{D}$, P_k^i
Output: d_k^i
begin
for $i = 1 : N$

$$K_i = \begin{cases} 0 & if\ \mathbf{s}(0) < P_k^i < \mathbf{s}(1) \\ 1 & if\ \mathbf{s}(1) < P_k^i < \mathbf{s}(2) \\ \vdots & \vdots \\ L-1 & if\ \mathbf{s}(L-1) < P_k^i < \mathbf{s}(L) \end{cases}$$

$$d_k^i = \mathbf{D}(K_i) \cdot \frac{\mathbf{s}(K_i+1)-P_k^i}{\mathbf{s}(K_i+1)-\mathbf{s}(K_i)} + \mathbf{D}(K_i+1) \cdot \frac{P_k^i-\mathbf{s}(K_i)}{\mathbf{s}(K_i+1)-\mathbf{s}(K_i)}$$

end for
end

D. LOCATION ESTIMATION BASED ON HIERARCHICAL VOTING

In the location estimation based on hierarchical voting, we first divide the $M \times M$ field into the corresponding $W \times W$ size cell with the precision of w, and use it as a voting matrix. For example, a 10m×10m field, if w =0.1, the size W is equal to 10/0.1=100. And the cell can be represented as $\mathbf{C}(m, n)$, for m, n=1,...,W. Let each cell correspond to an element in the voting matrix$\mathbf{V}(m, n)$. Then, voting is performed on the basis of the voting matrix, and the position of the mobile node is calculated by the accumulated values in the matrix. The positioning algorithm can be mainly divided into two steps: voting and positioning.

Step 1: We first calculate a parameter using the Gaussian distribution parameter of the measured noise. The parameter is the opposite of the value which corresponds to a probability of 0.125 in the Gaussian distribution function.

$$range = -\text{normin v}\left(0.125, 0, \sigma^2\right) \tag{8}$$

Then for each element, after calculating the distance between it and the beacon node, calculate the difference between the result and the measured distance:

$$\mathbf{e}_k^i(m, n) = \left| d_{imn} - d_k^i \right| \tag{9}$$

where $d_{imn} = \|\mathbf{c}_i - \mathbf{C}(m, n)\|$.

If $\mathbf{e}_k^i(m, n) > range$, using the following formula to accumulate the array in the voting matrix.

$$\mathbf{V}(m, n) = \mathbf{V}(m, n) + N\left(\mathbf{e}_k^i(m, n); \mu, \sigma^2\right) \tag{10}$$

where $N\left(\mathbf{e}_k^i(m, n); \mu, \sigma^2\right)$ denotes the Gaussian density function of $\mathbf{e}_k^i(m, n)$ with mean μ and covariance σ^2.

Step 2: When the voting is completed, the element containing the maximum value in the voting matrix $\mathbf{V}$ is denoted as $\mathbf{C}_i^* = [m^*, n^*]$, which meet$\mathbf{V}(m^*, n^*) \geq \mathbf{V}(m, n)$, for $m, n = 1, \ldots, W$. And then record the collection of all $\mathbf{C}_i^*$ as $\mathbf{C}^* = [\mathbf{C}_1^*, \ldots, \mathbf{C}_v^*]$, where v means the number of $\mathbf{C}_i^*$. Finally, the estimated position of the mobile node will be as follows:

$$\bar{\mathbf{C}}^* = \sum\nolimits_i^v \mathbf{C}_i^* \Big/ v \tag{11}$$

Figure 3 shows a 1.5m×1.5m field with w =0.1, M =15 and σ_i^2 =1. The blue and green dots represent the location of the beacon node and the final estimated location of the mobile node, respectively. In this measurement, the d_k^i is 5, 4, 5 respectively. And the number on each cell represents the cumulative value of each cell after voting. So the larger the cumulative value, the smaller the distance deviation.

We can summarize the location estimation based on hierarchical voting as the following pseudo code shown in Algorithm 3.

V. SIMULATION AND EXPERIMENT RESULTS

A. SIMULATION RESULTS

We first verify the performance of FHRQ through simulation. In the simulation, the beacon nodes are randomly deployed in

0	0	0	0.22	0.24	0.50	0.40	0.30	0	0	0	0	0	0.30	0.40
0	0.28	0.37	0.40	0.40	0.77	0.72	0.28	0	0	0	0	0	0	0.35
0.32	0.40	0.34	0.27	0.47	0.67	0.62	0.40	0.32	0	0	0	0	0	0.27
0.40	0.30	0	0	0.24	0.40	0.24	0.30	0.40	0.28	3	0	0	0	0.24
0.35	0	0	0	0.22	0.39	0.27	0	0.35	0.37	0	0	0	0	0.27
0.27	0	0	0	0	0.37	0.35	0	0.49	0.63	0.44	0	0	0	0.35
0.24	0	0	0	1	0.28	0.64	0.66	0.64	0.80	0.64	0.36	0.24	0.30	0.40
0.27	0	0	0	0	0.24	0.71	0.77	0.90	0.91	0.74	0.64	0.73	0.64	0.32
0.35	0	0	0	0	0.36	0.37	0.48	0.71	0.77	0.40	0.60	0.74	0.64	0
0.40	0.30	0	0	0.22	0.40	0.28	0.30	0.40	0.50	0.24	0.22	0.28	0.40	0.22
0.32	0.40	0.34	0.27	0.48	0.67	0.59	0.40	0.32	2	0	0	0.24	0.40	0.24
0	0.28	0.37	0.40	0.62	0.80	0.65	0.28	0	0	0	0	0.28	0.40	0.22
0	0	0	0.22	0.24	0.59	0.37	0.20	0	0	0	0.20	0.36	0.36	0
0	0	0	0	0	0.24	0.39	0.37	0.28	0.24	0.28	0.37	0.38	0.24	0
0	0	0	0	0	0	0.24	0.36	0.40	0.40	0.40	0.36	0.24	0	0

i Sensor Node

Mobile Node

FIGURE 3. An example of voting process (three beacon node).

Algorithm 3 Location Estimation based on Hierarchical Voting

Input:d_k^i
Output: $\bar{\mathbf{C}}^* = [\hat{x}_k, \hat{y}_k]^{\mathrm{T}}$
Initialization:$\mathbf{V} = 0$
begin
$range = -nor\min v\left(0.125, 0, \sigma^2\right)$
for i =1:N do
for m =1:W do
for n =1:W do
$d_{imn} = \|\mathbf{C}(m, n) - \mathbf{Z}_i\|$
$\mathbf{e}_k^i(m, n) = \left|d_{imn} - d_k^i\right|$
if $\mathbf{e}_k^i(m, n) > range$
$\mathbf{V}(m, n) = \mathbf{V}(m, n) + N\left(\mathbf{e}_k^i(m, n); \mu, \sigma^2\right)$
end if
end for
end for
end for
$\mathbf{C}_i^* = [m^*, n^*] = find\,(\mathbf{V} == \max(\max(\mathbf{V})))$
$\bar{\mathbf{C}}^* = \sum_i^v \mathbf{C}_i^* / v$
end

---

a region sized 15m×15m, and the default parameter values in the simulation are shown in Table 1.

We compare the proposed method with particle swarm optimization (PSO) method and the QDG-QRSS algorithm proposed in [22] which has been introduced in section 2 "Related Works". For each parameter condition, we will perform multiple simulations. And the performance of the proposed algorithm is measured by the cumulative distribution function (CDF) and the Root Mean Square Error (RMSE):

TABLE 1. The default parameter values.

Parameters	Symbol	Default Values
The number of beacon nodes	N	5
The number of cluster centers	L	10
The mean of measurement noise	μ	0
The standard deviation of measurement noise	σ	1
The path loss exponent under LOS situation	α	1.5
The path loss exponent under NLOS situation	α_{NLOS}	3
The NLOS error	$N\left(\mu_{NLOS}, \sigma_{NLOS}^2\right)$	$N(2,3^2)$

$$\mathrm{RMSE} = \sqrt{\frac{1}{K \cdot t_n} \sum_{i=1}^{t_n} \sum_{k=1}^{K} \left(\left(x(k) - \hat{x}_i(k)\right)^2 + \left(y(k) - \hat{y}_i(k)\right)^2\right)} \tag{12}$$

where $t_n = 40$, $K = 25$, $[x(k), y(k)]$ is the true position of the mobile node at time k, and $\left[\hat{x}_i(k), \hat{y}_i(k)\right]$ is the estimated position for $i - th$ trial at time k.

As shown in Figure 4, we randomly deploy 5 beacon nodes in the 15m×15m area, and one mobile node is moving in the area. In the figure, we select five positions in the motion trajectory of the mobile node, and compare the filtered effects of various algorithms. In the simulation process, we use 15m as the maximum communication distance between the two nodes, and the corresponding RSSI measurement value at 15m is the threshold. If the RSSI measurement is less than the threshold, the node is outside the communication distance, and no data will be returned to the FC. If the RSSI measurement is greater than the threshold, indicating that the node is within the communication distance, then the quantized data can be received by the FC and input into the

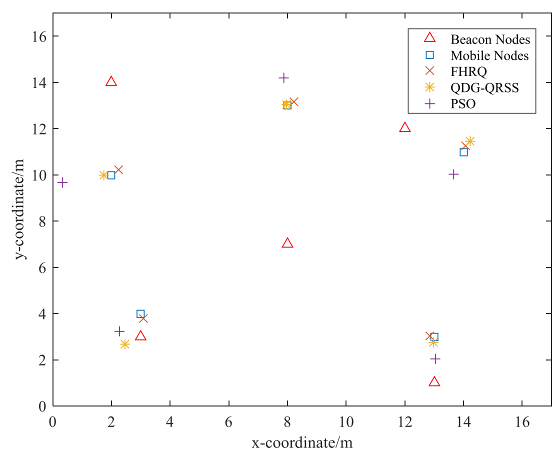

FIGURE 4. The deployment of beacon nodes and obstacles.

positioning algorithm. Then we can get the average localization errors of the PSO, QDG-QRSS, and FHRQ algorithms are 1.1919m, 0.4952m, and 0.2450m, respectively. So the proposed method has obviously better performance than the other methods.

In the following section, we investigate the effect of various parameters on the proposed method.

1) THE MEAN OF MEASUREMENT NOISE

Figure 5 shows the effect of the mean of measurement noise on the RMSE. We can see that the RMSE of all methods increases with the mean of measurement noise increase, and the proposed method has higher localization accuracy than PSO and QDG-QRSS at all time. We average all the cases and find that FHRQ is better than PSO and QDG-QRSS about 134.96% and 59.38%, respectively.

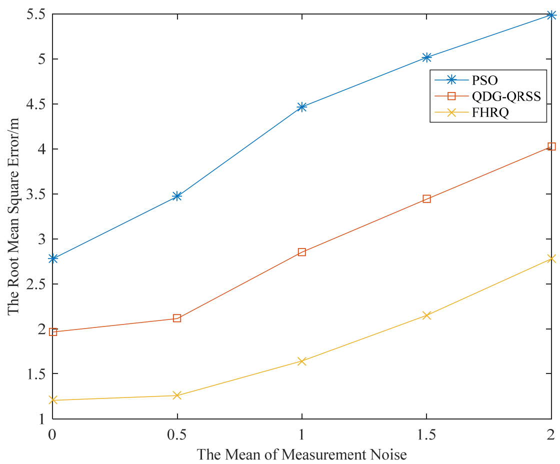

FIGURE 5. The mean of measurement noise versus RMSE.

Figure 6 shows the CDF graph of each algorithm when the mean value of the measured noise is 1. We can see that the proposed algorithm has the best effect, 90% of the error is less than 3.1m, and 90% of the errors of QDG-QRSS and PSO are less than 5.6m and 8.5m, respectively.

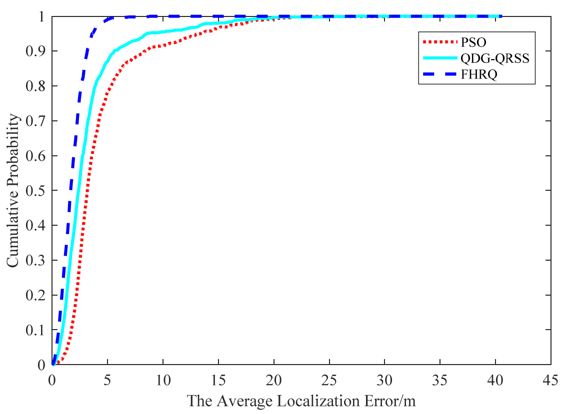

FIGURE 6. CDF of localization errors when $\mu = 1$.

2) THE STANDARD DEVIATION

Figure 7 shows the effect of the standard deviation of measurement noise on the RMSE. We can see that the RMSE of all methods increases with the standard deviation of measurement noise increase, but QDG-QRSS increases faster than PSO and FHRQ. At the same time, the FHRQ algorithm has better performance at all the time. When the standard deviation of measurement noise is 1, the proposed method has higher localization accuracy than PSO and QDG-QRSS, about 130.37% and 63.07%, respectively. When the standard deviation of measurement noise is 9, the proposed method has higher localization accuracy than PSO and QDG-QRSS, about 29.50% and 48.80%, respectively.

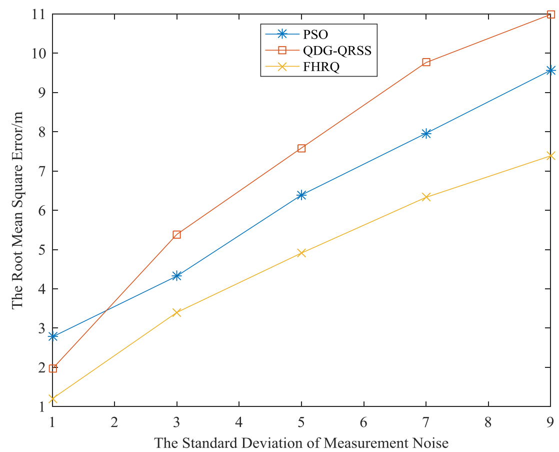

FIGURE 7. The standard deviation versus RMSE.

Figure 8 shows the CDF graph of each algorithm when the standard deviation of the measured noise is 1. The proposed algorithm is significantly better than PSO and QDG-QRSS, and the larger the error, the more obvious. With FHRQ positioning, 97% of the localization error are within 3m, while after QDG-QRSS and PSO positioning, there only have 83.2% and 77.3% within 3m.

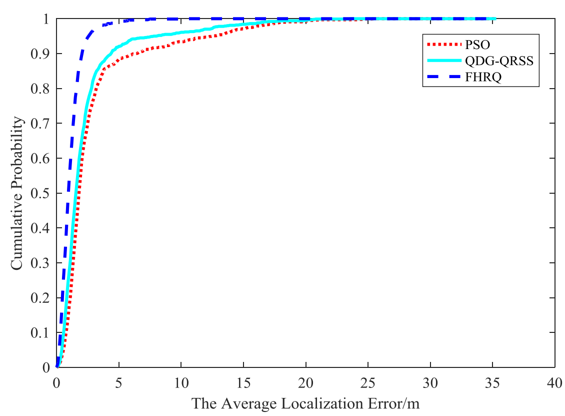

FIGURE 8. CDF of localization errors when $\sigma = 1$.

3) THE NUMBER OF CLUSTER CENTERS

Figure 9 shows the relationship between the performance of the proposed method and the number of cluster centers.

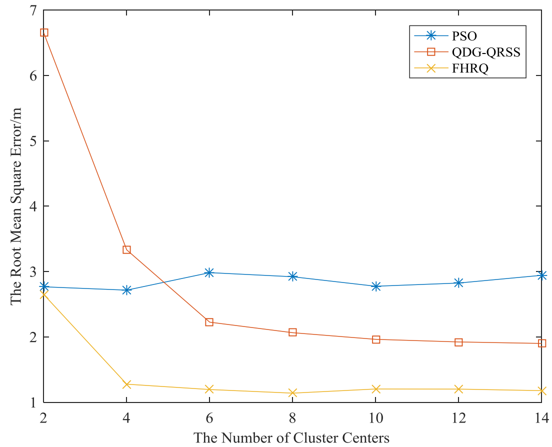

FIGURE 9. **The number of cluster centers versus RMSE.**

It can be observed that the RMSE of QDG-QRSS and FHRQ decreases at the beginning as the number of cluster centers increases, and then gradually stabilizes. And the proposed FHRQ algorithm has the highest localization accuracy, but PSO method owns the worst performance at most of the time. When the number of cluster centers is 8, the FHRQ method has higher localization accuracy than PSO and QDG-QRSS, about 149.49% and 61.19%, respectively.

Figure 10 shows the CDF graph of each algorithm when the number of cluster centers is 14. We can see that 90% of the positioning errors of the three algorithms are less than 1.9m, 3.2m and 5.9m, respectively. Our algorithm has 68.42% and 210.52% optimizations relative to QDG-QRSS and PSO, respectively.

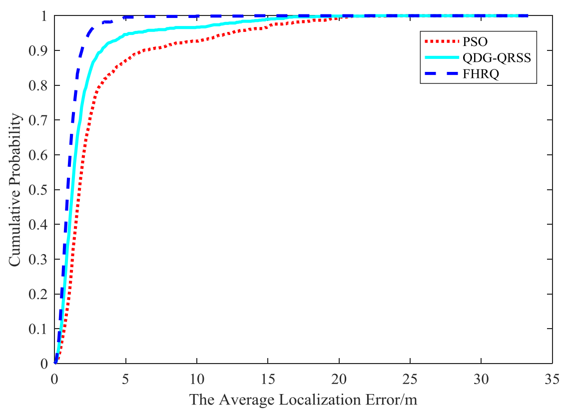

FIGURE 10. **CDF of localization errors when $L = 14$.**

4) THE NUMBER OF BEACON NODES

Figure 11 shows the relationship between the RMSE and the number of beacon nodes. We can see that the RMSE of all methods decreases with the number of beacon nodes increase. And the proposed method has higher localization accuracy than PSO and QDG-QRSS, about 136.17% and 74.59%, respectively.

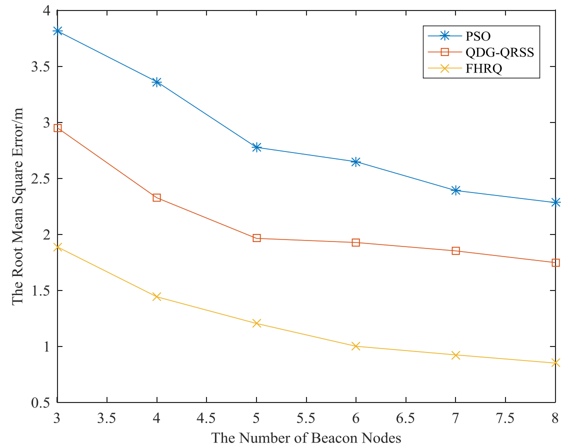

FIGURE 11. **The number of beacon nodes versus RMSE.**

Figure 12 shows the CDF graph of each algorithm when the number of beacon nodes is 8, and our algorithm has always been superior to PSO and QDG-QRSS in each interval. At the accumulated 90% positioning error of three algorithms, the proposed algorithm has 75% and 150% optimizations respectively with respect to QDG-QRSS and PSO.

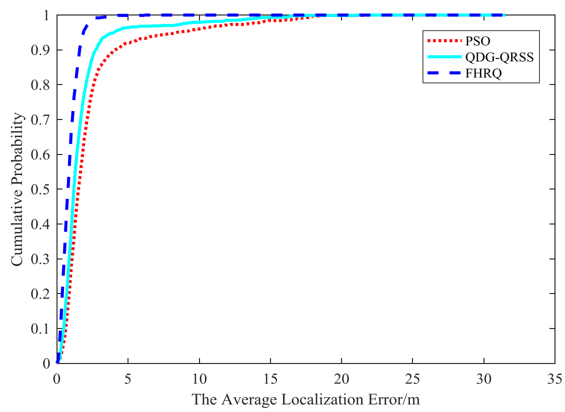

FIGURE 12. **CDF of localization errors when $N = 8$.**

5) DIFFERENT SHAPE OF A FUZZY MEMBERSHIP FUNCTION

At present, the shape of a fuzzy membership function that are widely used usually follow triangles, trapezoids, or single points curves. Through the experiment, we found that the triangle shape has the best positioning effect, so we follow the shape of triangles curve in this article. Table 2 shows the average localization error of each fuzzification scheme under the default parameters. It can be seen that our scheme has 5.69% and 33.72% optimizations relative to trapezoids and single points, respectively.

6) THE NLOS SITUATION

When we introduce NLOS error with a probability of 50%, Figure 13 shows the CDF of each algorithm. It shows that

TABLE 2. Comparison of Simulation Results.

Shape of the Fuzzy Membership Function	RMSE/m
triangles	1.1736
trapezoids	1.2404
single points	1.5693

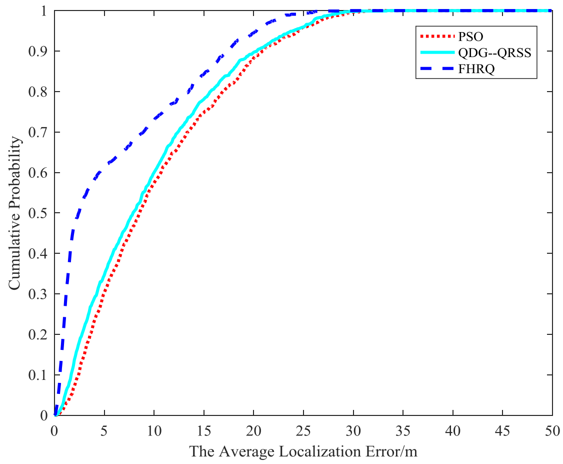

FIGURE 13. CDF of localization errors in NLOS situations.

the proposed algorithm has obvious advantages over other algorithms when the localization error is small, but when the error becomes larger, its performance will get worse. But as sixty percent of localization error of the PSO, QDG-QRSS and FHRQ algorithms are less than 10.8m, 10.1m and 4.6m, and the average localization error is 10.3m, 9.5m, 6.2m, respectively. It can be seen the FHRQ algorithm has the highest localization accuracy.

Figure 14 shows the effect of the ratio of NLOS errors in the measured data on RMSE. The RMSE of all methods increases as the ratio of NLOS errors increases. As can be seen from the figure, the proposed method has the best performance when the NLOS error ratio is small. But when the proportion of NLOS error is more than the LOS error, the filtering effect will get worse. And the QDG-QRSS algorithm will only achieve better results when the ratio of NLOS error exceeds 80%.

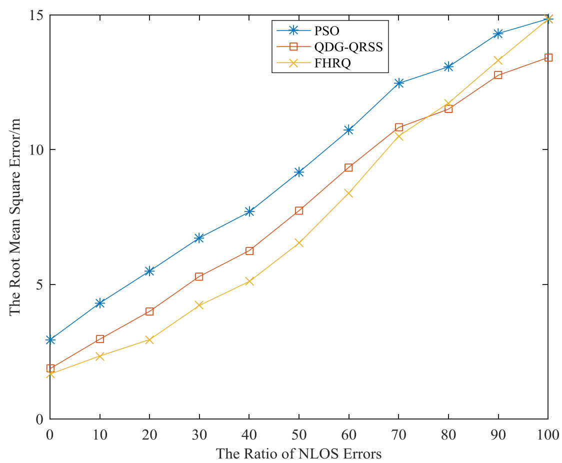

FIGURE 14. The ratio of NLOS errors versus RMSE.

From the Figure 14 we can see that the effect is best when the ratio of NLOS error is 40%. At this time, the corresponding CDF graph of each algorithm is shown in Figure 15. We can see that the proposed algorithm has great advantages in the interval where the localization error is small. Referring to Figure 14, we can find that the proposed algorithm can weaken the influence of NLOS error on the positioning result, especially when the proportion of NLOS error is small, the positioning accuracy can be greatly improved, but the effect will be worse when the NLOS error dominates the measured value.

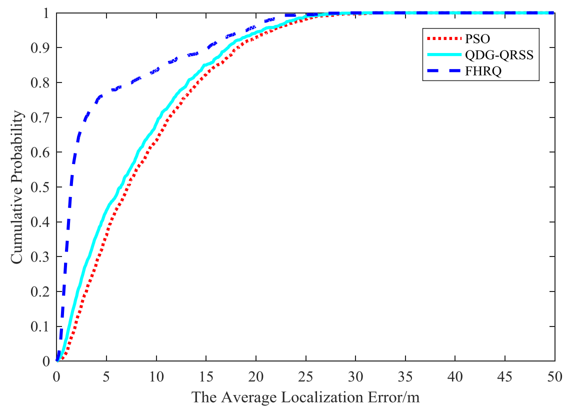

FIGURE 15. The average localization error versus CDF.

By counting the results of the simulation of each parameter, we can obtain Table 3 as shown below, and we can see the effect of the proposed algorithm on noise filtering and its good robustness.

TABLE 3. Comparison of simulation results.

μ	σ	L	N	NLOS/%	FHRQ/m	QDG-QRSS/m	PSO/m
0	1	10	5	0	1.205	1.965	2.776
2	1	10	5	0	2.776	4.203	5.489
0	9	10	5	0	7.386	9.565	10.99
0	1	14	5	0	1.18	1.902	2.944
0	1	10	8	0	0.8519	1.748	2.284
0	1	10	5	40	5.109	6.255	7.688

NLOS/% indicates the ratio of NLOS errors in the measured data, and FHRQ/m, QDG-QRSS/m, and PSO/m respectively represent the average error of the positioning results of the three algorithms.

B. EXPERIMENT RESULTS AND COMPUTATION TIME

1) EXPERIMENT RESULTS

After the simulation is over, we have carried out practical experiments to further verify the positioning performance of the proposed algorithm. The experimental equipment used for field experiments is mainly a mobile node and several beacon nodes. And the beacon node could measure the RSSI between the beacon node and the mobile node.

In the experiment, we composed multiple ZigBee nodes as beacon nodes and mobile nodes to form a sensor network, and use these nodes to measure the RSSI. We chose CC2530F256 as the solution for the system-on-chip of ZigBee nodes, which can build a sensor network at very low material cost. And because this system combines Texas Instruments' gold unit Z-Stack, we can easily obtain RSSI measurements. At the same time, we use the gateway board composed of STM32F051 and CH340 to transmit the data measured by the ZigBee node to the computer. A complete gateway board plus a ZigBee node is shown in Figure 16:

FIGURE 16. The complete hardware we use.

The CC2530, which we chose as the ZigBee solution, not only has Z-Stack support on the software system, but also has great advantages in hardware. It has the performance of leading RF transceivers, an industry-standard enhanced 8051 CPU, 8-KB RAM, in-system programmable flash and many other powerful features like ADC and USART that allow him to maintain ultra-low power while still having powerful performance. At the same time, it has four different flash versions with 32/64/128/256KB flash memory respectively. And it also has different operating modes, the short transition time between operating modes makes it especially suitable for systems with ultra-low power requirements.

In the actual experiment, we use the zigbee 2007 pro protocol stack built in CC2530 to build the mesh network, so that the RSSI measurement received by each node can be transmitted to the FC. And the main transmission parameters of the CC2530 are shown in the following Table 4:

In the experimental environment, at the height of 1m from the ground, there are 8 beacon nodes and one mobile node deployed in a plane of 3m×3m, and mobile node moves around a rectangle table in uniform velocity following a rectangle trajectory as shown in Figure 17.

In order to reduce the influence of environmental changes on the parameters of the RSSI model, we first use the environmental adaptive RSSI parameter estimation method [29] to obtain the parameters of the RSSI model before measurement. We use a beacon node to send signals, arrange additional beacon nodes according to a specified distance,

TABLE 4. CC2530 main transmission parameters.

Parameter Name	Performance
Frequency Range	2405MHz-2485MHZ
Transmission Rate	250kbps
Receiving Sensitivity	-97dBm
Transmit Rower	3.8-4.2dBm
Number of Channels	16

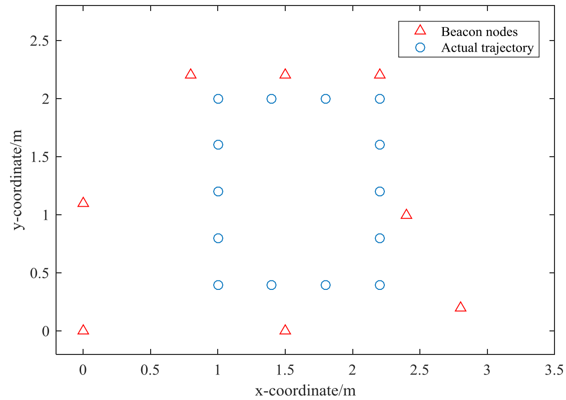

FIGURE 17. The deployment plan for the test.

and measure the received RSSI parameters. Since the distance between the beacon nodes is known, we can plot the measured RSSI as a function of distance and fit the parameters by least squares. The final result is shown in Figure 18.

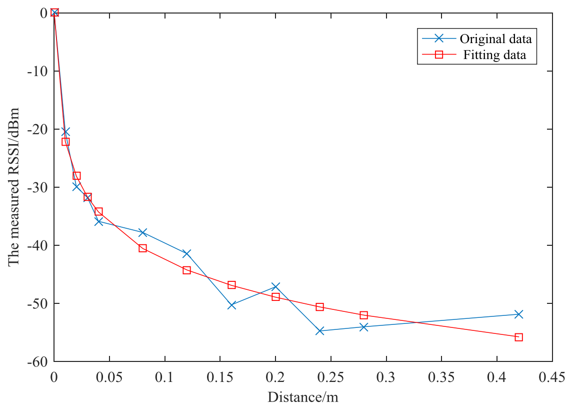

FIGURE 18. The curve between RSSI and distance.

Then, during the positioning process, 45 RSSI measurements are taken at each node to reduce the effect of noise on the positioning accuracy. At the same time, the measurement frequency of ZigBee is set to 20HZ. The trajectories obtained after filtering by various algorithms are shown in Figure 19. In compared with other algorithms, we can obviously see that the trajectory of the FHRQ is closer to the true trajectory.

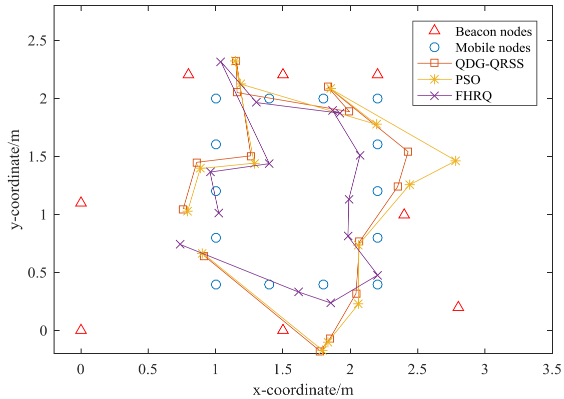

FIGURE 19. The positioning effect of each algorithm.

And the positioning error of each algorithm varies with the number of cluster centers as shown in Figure 20. We can see from the figure that the more the number of gradations, the effect of QDG-QRSS algorithm will gradually become better until it stabilizes. And the proposed method has the best performance at most of the time. When the grading number is 13, all algorithms have reached their optimal situation, we can get the average positioning error of PSO, QDG-QRSS and FHRQ algorithm is 0.3515m, 0.4025m and 0.3043m, respectively. We can see that the QDG-QRSS method is less effective due to the larger variance of the measured noise, and the proposed method has the best performance.

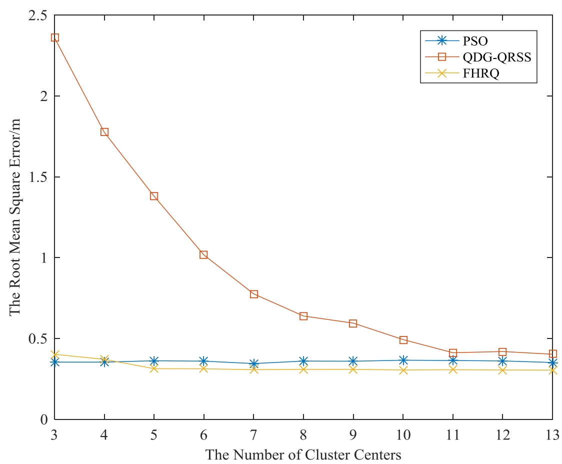

FIGURE 20. The number of cluster centers versus RMSE in practical experiment.

The CDF of localization error in our practical experiment is shown in Figure 21. It shows that when the localization error is small, the proposed algorithm has obvious advantages over other algorithms, and ninety percent of localization error of the PSO, QDG-QRSS and FHRQ algorithms are less than 0.64m, 0.69m and 0.56m. It can be seen the FHRQ algorithm has the highest localization accuracy.

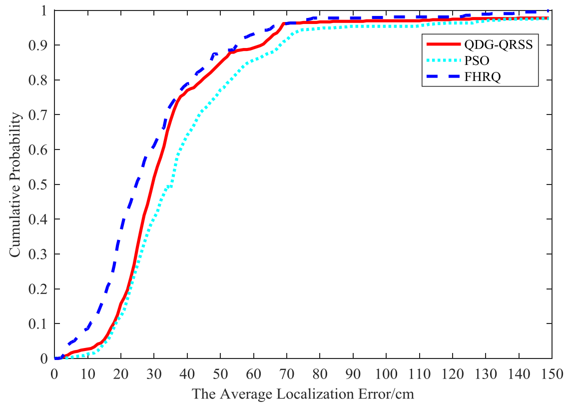

FIGURE 21. CDF of localization errors in practical experiment.

TABLE 5. Running times of each method.

Method Used	Running Times/s
PSO	0.0051
QDG-QRSS	0.0089
FHRQ	0.0530

2) COMPUTATION TIME

Table 4 shows the running times of the PSO, QDG-QRSS and FHRQ. The three methods are coded using Matlab 2016a and tested on a Windows 10 Professional workstation with Intel(R) Core(TM) i7-8750U CPU @ 2.20GHz and 8.00GB RAM. Although FHRQ consumes more time, the time for a single processing is still less than the interval between single samples (the sampling frequency is 10Hz). Therefore, the algorithm can be applied for online tracking.

VI. CONCLUSIONS

This paper proposes a positioning algorithm based on fuzzy logic and hierarchical voting, which aims to realize the positioning of mobile nodes in mixed LOS and NLOS environments. The FCM algorithm is used to calculate the quantization threshold. This method only needs the signal propagation parameters under LOS conditions, and does not need any prior information about NLOS errors, and is robust to NLOS errors. At the same time, the proposed hierarchical voting based positioning algorithm has a good effect. The simulation results show that the proposed algorithm can effectively reduce the noise interference, no matter the measurement noise is large and the measurement noise is small. And regardless of the proportion of the NLOS error involved, the proposed method can achieve higher positioning accuracy. In actual experiments, the performance of this method is also better than QDG-QRSS and PSO. And it is robust to NLOS error.

For future work, we will consider the effect of small-scale fading due to multipath as the system model may not be accurate. More experiments will be conducted to focus on the localization under these imperfect situations and extend the proposed method to deal with multiple mobile nodes.

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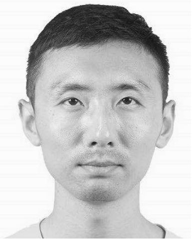

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