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RFID 3D-LANDMARC Localization Algorithm Based on Quantum Particle Swarm Optimization

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Abstract: Location information is crucial in various location-based applications, the nodes in location system are often deployed in the 3D scenario in particle, so that localization algorithms in a three-dimensional space are necessary. The existing RFID three-dimensional (3D) localization technology based on the LANDMARC localization algorithm is widely used because of its low complexity, but its localization accuracy is low. In this paper, we proposed an improved 3D LANDMARC indoor localization algorithm to increase the localization accuracy. Firstly, we use the advantages of the RBF neural network in data fitting to pre-process the acquired signal and study the wireless signal transmission loss model to improve localization accuracy of the LANDMARC algorithm. With the purpose of solving the adaptive problem in the LANDMARC localization algorithm, we introduce the quantum particle swarm optimization (QPSO) algorithm, which has the technology advantages of global search and optimization, to solve the localization model. Experimental results have shown that the proposed algorithm improves the localization accuracy and adaptability significantly, compared with the basic LANDMARC algorithm and particle swarm optimization LANDMARC algorithm, and it can overcome the shortcoming of slow convergence existed in particle swarm optimization.

Keywords: three-dimensional localization algorithm; LANDMARC; RBF neural network; QPSO

1. Introduction

With the development of mobile communication technology and the increasing of business requirements, the application of location-based services has attracted more and more attention, indoor localization is a very important research subject for various location-based applications [1]. The indoor localization with low complexity and high accuracy is one of the main challenges in today's wireless world [2]. In order to provide positioning and navigation in the indoor environment, various methods based on different technologies such as WSN-based networks [3,4], WIFI network [5,6], and RFID localization technology [7,8] have been proposed and developed. Among various indoor localization schemes, RFID technology has obtained more and more interest in localization systems development for its low cost, easy deployment, and successful utility in harsh environments in recent years [9].

Radio frequency identification (RFID) is a kind of through the wireless signal to identify specific targets and read data wireless communication technology [10]. A variety of localization techniques have been proposed in the literature, which differ from each other because of the different types of underlying techniques used. The RFID localization algorithms can be simply classified into two categories: range and range-free methods. The important ranging techniques include time of arrival (TOA) [11,12], time difference of arrival (TDOA) [13], angle of arrival (AOA) [14], phase of arrival (POA) [15], phase difference of arrival (PDOA) [16], and received signal strength (RSS) [17]. The localization accuracy of the ranging algorithm is determined by the ranging accuracy, and the

different ranging methods that vary in performance. For example, the TOA ranging method can achieve high accuracy of ranging in the line-of-sight (LOS) and multipath environment, but it needs accuracy of high clock synchronization which is expensive between the transmitting end and receiving end [18]. The TDOA technique avoids the transmitter–receiver synchronization problem and measures the different arrival times of the transmitted signal at multiple receivers, requiring a precise time reference between the receivers [19]. The AOA technique calculates the intersection of several direction lines with directional antennas or an antenna array, requiring complex and expensive devices and suffering from multipath effect and shadowing. The POA method has a problem of having whole cycle phase ambiguity in calculation [20]. The common range free method is fingerprinting [21]. For example, the well-known LANDMARC [22] is based on fingerprinting localization algorithm, it used WKNN method to locate the target tag based on the RSS. However, it used active reference tags to replace the fingerprint points for RFID localization, because the reference tags and the target tags are in the same environment, for the range-free method, it can overcome the multipath and NLOS to some degree, although the cost of active tag is higher than the passive tag.

LANDMARC localization algorithm according to space can be divided into two categories, one is 2D-LANDMARC, one is 3D-LANDMARC. Since in practice, the nodes in location system are often deployed in the 3D scenario, such as a warehouse, the localization in a three-dimensional environment is more realistic and localization algorithms in a three-dimensional space are necessary [23]. Literature [24] proposed a 3D-LANDMARC algorithm, by arranging the reference labels of the two-dimensional plane into the three-dimensional space. However, it did not consider the influence of the difference between the three-dimensional space and the two-dimensional plane on the performance of the algorithm, resulting in a large localization error so that cannot meet the requirements of high localization accuracy. Accordingly, literature [25] combined the RSS-based ranging algorithm with the 3D-LANDMARC algorithm to replace the signal strength in the 3D-LANDMARC algorithm with distance to improve the accuracy of the LANDMARC algorithm in 3D spatial location, but the use of the distance measurement model does not have the ability to adapt to the dynamic environment so that it increases the probability of misuse reference label and affects the positioning accuracy. In order to improve the localization accuracy of LANDMARC and its improved algorithm, [26] introduced the particle swarm optimization (PSO) algorithm into the indoor location of RFID, and the position of the virtual tag is calculated by the PSO algorithm, to determine the coordinate of the measuring tags. This method improves the localization accuracy, but the PSO has a slow convergence rate and is easy to fall into the local optimal solution.

Therefore, the 3D localization algorithm based on 3D-LANDMARC needs to improve the localization precision, the adaptive ability and the convergence speed of the optimization algorithm in the application process. The radial basis function (RBF) neural network is employed as approximation function that maps RSS fingerprints to user locations in [27]. It is proved by two indoor positioning systems in WLAN and GSM environment based on RBF neural networks that the RBF neural network can get the nonlinear fitting relationship between the received signal intensity and the transmission distance in different environments, resulting in improving the localization accuracy of 3D-LANDMARC. In [28], a PSO-based LANDMARC indoor localization algorithm is proposed, which contains the following two aspects. It adopts a Gaussian smoothing filter to process received signal strength indicator (RSSI) values, which can reduce the impact of environmental factors on the position estimation effectively. Furthermore, PSO algorithm is introduced to obtain a better positioning result. The report [29] verified the feasibility of indoor positioning method based on particle swarm through concrete experiments. Experimental results show that good accuracy is obtained in all considered cases, especially when the proposed PSO based localization algorithm is applied to stochastic corrected distances. In [30], it is proved that quantum particle swarm optimization (QPSO) shows better adaptive ability and iteration speed than PSO. Combining the advantages of RBF neural network and QPSO algorithm, this paper proposed an improved 3D-LANDMARC, which can improve

the performance of the 3D-LANDMARC localization system in localization accuracy, self-adapting ability, and optimizing convergence speed.

The remaining part of this paper is structured as follows. In Section 2, we introduced some details of the 3D-LANDMARC algorithm and provided improvement strategies. In Section 3, the details of labels solution based on QPSO are described. The results of numerous experiments and performance evaluation are presented in Section 4. Finally, we conclude this paper in Section 5.

2. 3D-LANDMARC

2.1. 3D-LANDMARC Localization Algorithm

The 3D-LANDMARC localization algorithm is based on the centroid algorithm using RSSI, and its localization system layout is shown in Figure 1. The localization system consists of a number of known reference labels, unknown testing labels, and readers.

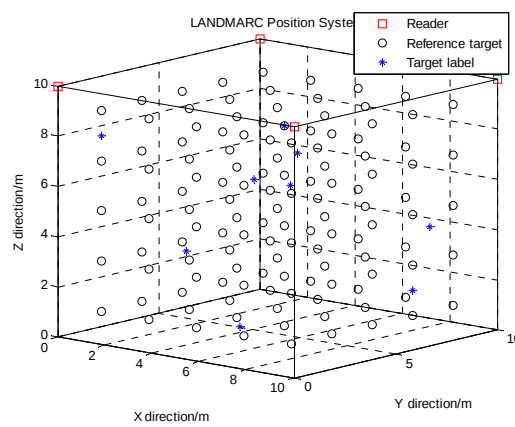


Figure 1. LANDMARC localization system layout.

The specific localization algorithm is described as follows [24]:

- (1) Set the number of readers is k , the number of testing labels is P , the number of reference labels is M , and record the location of each reference label coordinates
- (2) Each reader collects the signal strength vectors of all of the reference tags respectively

$$\vec{\theta}_i = (\theta_{i1}, \theta_{i2}, \dots, \theta_{ik}), \quad 0 < i \leq M \quad (1)$$

- (3) Select a testing label to be measured, record the signal strength vector of the testing label from k readers.

$$\vec{S} = (S_1, S_2, \dots, S_k) \quad (2)$$

- (4) The relative distances between the reference labels and the testing labels are expressed in Euclidean distance

$$E_i = \sqrt{\sum_{j=1}^k (DR_{ij} - DL_j)^2} \quad 0 < i \leq M \quad (3)$$

where DL_{ij} is the distance between the reference label i and the reader j , and DL_j is the distance from the testing label to the reader j , which can be obtained from the relationship between the signal strength and the distance in the signal transmission model.

- (5) The m reference labels with the smallest Euclidean distance are selected as nearest neighbor reference labels.

- (6) The weight of each nearest-neighbor reference label is calculated

$$w_i = \frac{1/E_i^2}{\sum_{i=1}^m 1/E_i^2} \quad 0 < i \leq m \quad (4)$$

- (7) The coordinate of the testing label is estimated from the weights and the coordinates of the nearest reference labels.

$$(x, y, z) = \sum_i^m w_i (x_i, y_i, z_i) \quad (5)$$

- (8) Repeat (3)–(7) and then estimate all the coordinates of the testing labels.

2.2. Improved 3D-LANDMARC Localization Algorithm

It can be seen that the localization algorithm is divided into two stages that selecting adjacent reference labels and determining the coordinates of the tested label depend on the reference label through the analysis of 3D-LANDMARC localization system. However, the 3D-LANDMARC algorithm has the problem that the probability of misplacing the adjacent reference labels is large when the adjacent reference label is being selected, and the localization accuracy of the centroid algorithm is limited and is dependent on the reference labels and weights when the reference labels are used to determine the coordinates of the reference labels. The strategies as follows are proposed to improve these two stages.

2.2.1. Select the Neighboring Reference Labels

From (3), we can see that the distance error of the testing label to reader directly influences the selection of the adjacent reference label. The non-linear relationship between the signal strength value and the distance between the reader and the label is shown below [27]

$$RSSI = -(10n \log_{10} d + A) \quad (6)$$

where A is the average signal strength value received from the signal source 1 m; n is the signal transmission loss factor, determined by the environment, $RSSI$ represents the collected signal strength value, and d is the distance from the receiver to the source.

RBF neural network shows a good advantage of nonlinear fitting, and uses the RBF neural network to fit the non-linear relationship between the signal strength value and the distance between the reader and the label in order to get the accurate adjacent reference label, the fitting training model is shown in Figure 2. The input layer is the label signal strength value collected by the reader, and the output layer outputs the corresponding distance value, the data of the reference tag is used as the training sample, and the distance between the testing label and the reader is outputted.

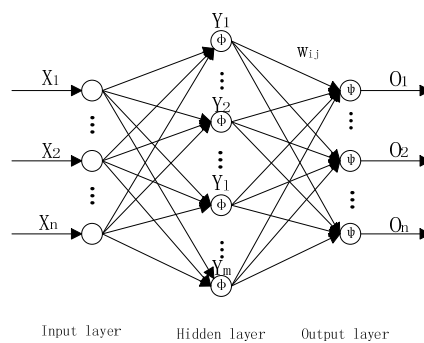


Figure 2. RBF neural network training model.

2.2.2. Testing Label Coordinate Problem Optimization

It can be seen from Equation (3) that 3D-LANDMARC uses the relative distance between the reference label and the testing label, the problem of localization of the testing label can be transformed into the problem of minimizing the distance error between the testing label and the reference label, which becomes the optimization problem. It can reduce the dependence of the localization result on the reference label coordinate and its weight and enhance the adaptive performance of the algorithm. The objective function $f(X)$ can be defined as

$$f(X) = \min \left(\sqrt{\frac{1}{m} \sum_{i=1}^m (\sqrt{(x-x_i)^2 + (y-y_i)^2 + (z-z_i)^2} - E_i)^2} \right) \quad (7)$$

where (x, y, z) are the coordinates of testing label; (x_i, y_i, z_i) are different reference label coordinates; m is the number of reference labels; E_i is the Euclidean distance which stands for relative position between the reference label and the testing label.

3. 3D-LANDMARC Optimization Goal Solution Based on QPSO

The adjacent reference label coordinates obtained by fitting RBF neural network in Section 2.2.1 are substituted into Equation (7), the particle is the testing label, and the coordinate of the testing label is the position of the particle. In this section, the positions of particles are evaluated by $f(x)$, and optimized by quantum particle swarm optimization algorithm. The optimal particle position is the estimated coordinate of the testing label.

3.1. QPSO Algorithm

The main idea of QPSO [28] is to use the wave principle of the particles in the quantum space. Based on the wave principle, the QPSO is realized effectively. The iteration process of QPSO is described as the following. First, initialize the states of the particles, and then the particles search for the global optimum in search space according to the wave function. The particle in QPSO could move and appears anywhere in the search space with a certain probability. The particles update their states according to the following equations without using velocity information:

$$mbest = \left(\frac{1}{N} \sum_{i=1}^N p_{i1}, \frac{1}{N} \sum_{i=1}^N p_{i2}, \dots, \frac{1}{N} \sum_{i=1}^N p_{id} \right) \quad (8)$$

$$p_i(t+1) = \varphi * p_i(t) + (1 - \varphi) * p_g \quad (9)$$

$$x_i(t+1) = p_i(t+1) \pm \alpha |mbest - x_i(t)| * \ln\left(\frac{1}{u}\right) \quad (10)$$

where, $mbest$ is the mean state and $p_i(t+1)$ contains the personal best of a particle and the global best. N is the number of particles. φ and μ are two random numbers uniformly distributed on $(0, 1)$. The only parameter α , called the 'creativity coefficient', is used to balance the local and global search of the algorithm during the iteration process.

Both experiment and theory has proved that the QPSO can overcome the shortcoming of standard PSO and outperforms standard PSO.

3.2. 3D-LANDMARC Optimization Goal Solution Based on QPSO

Each particle is thought as the estimated value of the testing label in the solving process of Quantum particle swarm optimization algorithm, $f(x)$ in Equation (7) is the fitness function of the particle. The localization algorithm proposed in this paper is shown in Figure 3, the main operations are

- (1) Data collection. The reader sends a signal of certain intensity, collects and records the return signal strength value from the label, collects several times consecutively, finds its statistical average as the final test data.

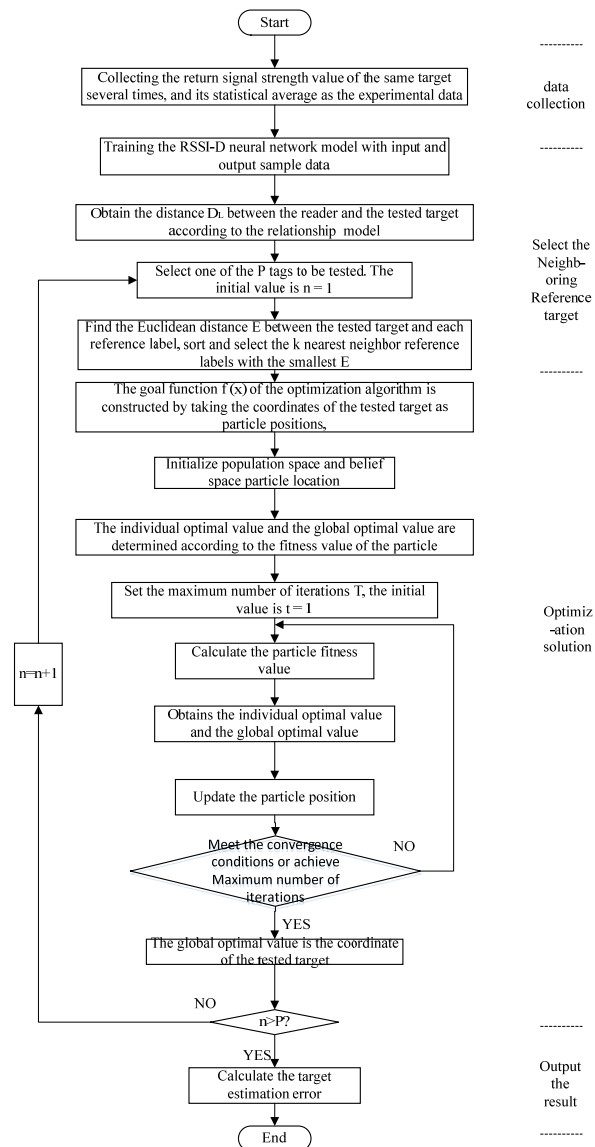


Figure 3. 3D-LANDMARC coordinate solution flowchart of quantum particle swarm.

- (2) Construction of signal transmission model. The distance between the reference tag and the reader is taken as the output sample data, and the nonlinear fitting relation model of the RSSI-D is obtained through the RBF neural network training, and the test data is taken as the input sample data. The distance between the tag and the reader is obtained by using the obtained relational model.
- (3) According to Equation (3), obtain the relative distance between the reference label and the testing label, and select four label whose distance are smaller as the adjacent reference label.
- (4) Substituting the coordinates of the adjacent reference label and the distance between the testing label and the adjacent reference label into Equation (7) to construct the objective function equation.
- (5) We use the quantum particle swarm algorithm to get the optimal solution of the objective function, it is thought of as the final estimated position of the label to be located.

4. Experimental Simulation Analysis

4.1. RFID Three-Dimensional Localization Examples

In this paper, we look at an RFID warehouse three-dimensional localization system as an example to be studied. The warehouse RFID localization system mainly consist of the reader, the known reference label, the unknown testing label, the layout shown in Figure 4, it is abstracted out based on the actual environment. In a $10 \times 10 \times 5$ m warehouse, there are five rows of shelves, each row of shelves is divided into four layers averagely and its length is 8 m, width is 1 m, height is 4 m, the width of the aisle is 1 m between two rows of shelves. The reader is fixed in the four corners of the warehouse, the reference labels are evenly distributed on the shelves, each surface of cargo is affixed with the information stored in the label to mark the location of the goods.

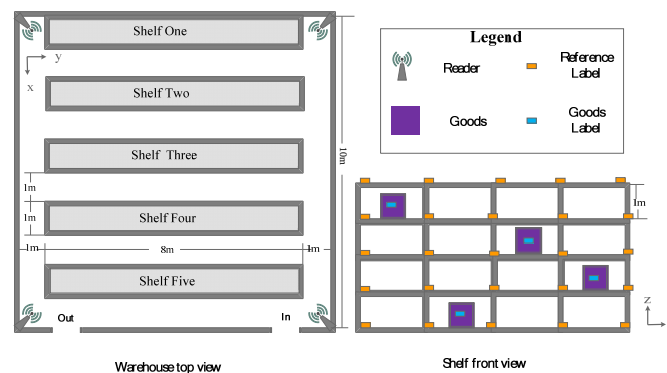


Figure 4. Warehouse abstract layout.

4.2. Localization Process and Results Analysis

4.2.1. Localization Algorithm Experiment Setup

Specific experiments are: In the warehouse shelves shown in Figure 4, 20 goods are randomly selected as the items to be positioned, and the common 3D-LANDMARC algorithm, particle swarm optimization LANDMARC algorithm (PSO-LANDMARC), and quantum particle swarm optimization LANDMARC algorithm (QPSO-LANDMARC) are used to locate the goods separately. All the algorithms should run 20 times, the iteration times of each optimization algorithm were 50 times, and the localization error and localization algorithm performance were analyzed respectively.

4.2.2. Experiment Content

(1) Experimental Results and Comparative Analysis of the Accuracy of Localization Algorithm

Figure 5 is the statistical results of error distribution, abscissa represents the error value, the vertical axis represents the proportion of the total number of labels that the error less than the corresponding error of the abscissa. It can be seen from the figure that the percentage of the QPSO-LANDMARC algorithm has a positional error of less than 0.56 m is 65% and the PSO-LANDMARC algorithm is 35% in the same error range while the percentage of the 3D-LANDMARC algorithm only reached 25%. It can be seen that the QPSO-LANDMARC algorithm can obtain more labels with less error. The algorithm has certain advantages over other two algorithms in locating accuracy.

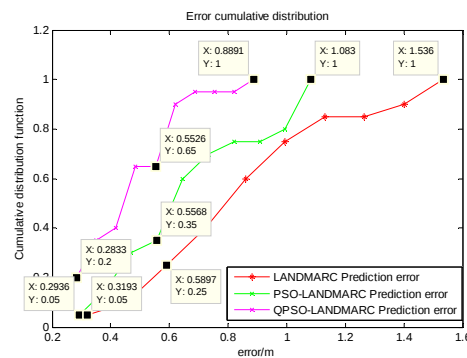


Figure 5. Error cumulative distribution.

(2) Experimental Results and Comparison of Self-Adaptive Ability of Localization Algorithm

As shown in Figure 6 for the localization error of the 20 labels obtained under the three algorithms, abscissa represents the number of the labels, vertical axis represents the value of localization error. Figure 7 is a graph of the minimum, mean, and maximum values of the errors in Figure 6, with the abscissa being the three localization algorithms, and the ordinate indicating the error value. It can be seen from the figure that the localization error of QPSO-LANDMARC algorithm fluctuates is between 0.25–0.92 m, the localization error of PSO-LANDMARC algorithm fluctuates is between 0.25–1.13 m, and the localization error of 3D-LANDMARC algorithm is between 0.25–1.6 m. From the experimental results, it can be seen that the QPSO-LANDMARC algorithm is significantly lower in position error and lower in volatility compared with the 3D-LANDMARC algorithm and the PSO-LANDMARC algorithm, and the adaptive ability is better.

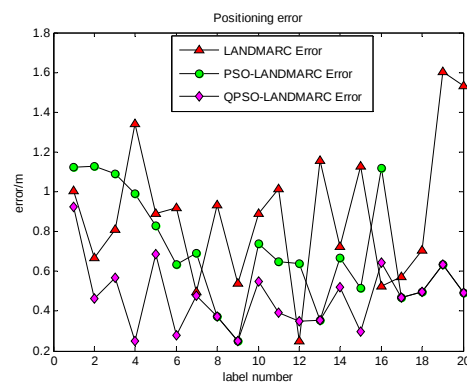


Figure 6. Localization error map.

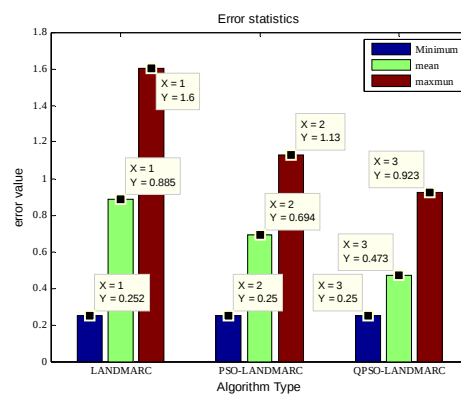


Figure 7. Localization error statistics.

(3) Experimental Results and Comparison of Convergence Rate of Localization Algorithm

Figure 8 is the comparison and analysis of the convergence rate of finding the best particle under the two optimization algorithms, the abscissa is the number of iterations, the vertical axis represents the fitness value of the particle. The figure shows that the number of iterations required for different optimization algorithms to reach the minimum of fitness. It can be seen from the figure that the fitness value of PSO-LANDMARC algorithm begins to be smooth when the number of iterations reaches 11 times, and after 7 iterations, the QPSO-LANDMARC algorithm gets a minimum of 0.02 less than the PSO-LANDMARC algorithm. Therefore, QPSO algorithm converges faster than PSO algorithm and QPSO algorithm, and finds the optimal value more frequently, which is better for the LANDMARC algorithm.

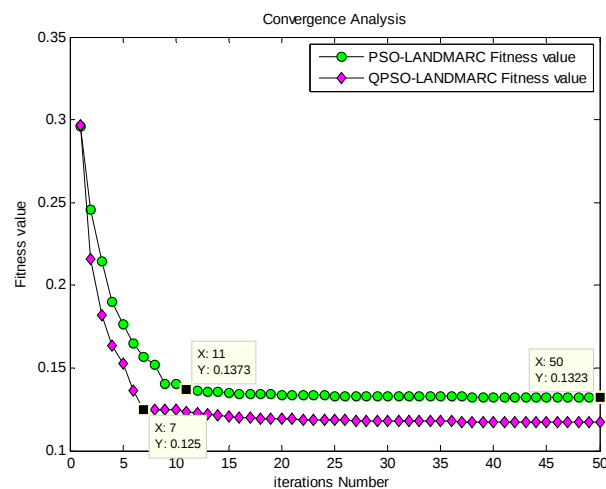


Figure 8. Convergence analysis.

5. Conclusions

The algorithm proposed in this paper is based on the LANDMARC localization algorithm, which uses the advantages of nonlinear fitting of the RBF neural network to get the wireless signal transmission loss model in the warehouse. By selecting the adjacent reference label accurately and combining it with the quantum particle optimization problem, the optimization algorithm is used to solve the position of the tested label. From the experimental results we can see that the number of tags employing the proposed QPSO-LANDMARC algorithm shows an average positioning error 0.2 m less than the average error employing the PSO-LANDMARC algorithm. Furthermore, the number of iterations using the QPSO-LANDMARC algorithm is only half that of the PSO-LANDMARC algorithm. The algorithm proposed in this paper exhibits higher localization accuracy and better adaptive ability than 3D-LANDMARC algorithm, and shows faster convergence speed than PSO-LANDMARC algorithm. Therefore, the proposed algorithm can improve the localization accuracy of the cargo based on the characteristics of the original algorithm.

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Conflicts of Interest: The authors declare no conflict of interest.

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