

Research on Indoor Localization Algorithm Based On Particle Swarm Optimization Algorithm in RFID

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Abstract

Indoor localization algorithm has low precision and high cost. Based on the VIRE algorithm, this paper proposes a RFID technology based on particle swarm optimization algorithm. Firstly, the improved threshold of wavelet algorithm to the read signal for de-noising and reduce the signal strength value fluctuations generated error; and then the weighted localization to improve the positioning accuracy of the virtual tags; at last, the particle swarm algorithm to identify the label virtual optimal solution. Simulation experiments show that the algorithm can effectively improve the location accuracy, time can be reduced.

Keywords: VIRE, Particle Swarm, RFID, Wavelet, Weighting

1. Introduction

Along with the development of wireless Internet technology and networking technology, and indoor wireless location technology more attention. At present, due to poor global positioning system (GPS) in the indoor positioning effect, the localization performance far cannot meet the requirements of people's work and life. At present, indoor positioning technology mainly includes infrared, ultrasonic, IEEE802.11 wireless positioning and positioning of radio frequency identification (RFID) technology. The radio frequency identification (RFID) is a kind of through the wireless signal to identify specific targets and read data wireless communication technology, has the advantages of low cost, non-contact, non-line of sight (NLOS) and high positioning precision and has been paid more and more attention. Currently typical RFID indoor positioning methods are mainly 3D-ID [1], SporON [2], LANDMARC [3]. Literature [1] orientation accuracy can reach 1-3m, but need to spend a certain cost; [2] can be widely used in 3D space, but system architecture still in the design; [3] by cheap RFID tags to replace expensive RFID reader localization, achieved good results, but need to intensive reference to assist, has certain limitations. Domestic and foreign scholars have carried on research, literature [4] proposed a using RFID indoor location algorithm based on BP neural network, the algorithm is introduced the reference tags assisted positioning, using BP neural network to establish the signal field intensity transformation model. Literature [5] proposed an improved nearest neighbor algorithm, by screening the selected adjacent reference tags to achieve recently adjacent labels in the optimal selection. Literature [6] mainly use Chan algorithm to locate the initial position estimation is obtained, the results as a Taylor series expansion method of the initial value, then makes use of the gradient decline on the establishment of the error function approximation calculation, combined with RFID technology to realize the indoor three-dimensional model. Literature [7] proposed a power adjustable dynamic positioning method, and convenient in the localization process in real-time observation of the reader to read reference label and target label, design the dynamic positioning Mat lab GUI interface, achieved certain results. Literature [8]

proposed a RFID indoor location algorithm based on neural network based on fuzzy, the algorithm will reference tag data as training samples of the neural network, to establish "label received signal strength and label reading and writing device distance mapping model RSSI-DIST". Then the least square solutions to determine target coordinates. TDOA hyperbolic positioning method is proposed in the literature [9]. The method using RF signal TDOA, with the precise time difference to measure the distance between the radio frequency (RF) labels and target, then hyperbola location algorithm to locate the target with the aid of the. Literature [10] proposed the use of label position distribution characteristic as prior information to improve the positioning accuracy, based on time of arrival (TOA) two-step weighted least squares method from the maximum likelihood estimation extended to minimum mean square error estimation is deduced, and based on the minimum mean square error estimation of TOA location method of the Cramer Rao lower bound (CRLB) and variance theory.

Based on the study VIRE [11] algorithm, using a reference label for large quantities, border positioning identified herein, this paper uses improved algorithms for signal threshold wavelet denoising read, reduced signal intensity values fluctuate produce the error, it can be consistent with the actual position of the RFID tag, then using particle swarm algorithm to locate RFID, can effectively avoid the VIRE algorithm pending label positioning error is large.

2. Signal Denoising

In the indoor environment, a certain period of time within a tag can be different RSSI value received, indoor video signal with high noise pollution, easily lead to the RSSI value has some volatility, thus affecting the signal stability. The reader obtains the RSSI value of the tag and the distance between the two is calculated according to the formula (1).

$$PL(d_1) = PL(d_0) + 10 \times n \times \lg\left(\frac{d_1}{d_0}\right) \quad (1)$$

In the formula (1), PL is refers to the path loss, n for path loss parameter, d_1 is the distance between the reader and tag, d_0 is the reference distance, $PL(d_1)$ is the reference of path loss apartment in d_1 . Since the RSSI value suffers from the influence of noise easily on the actual value deviation. Therefore, the improved wavelet threshold algorithm to perform the signal processing. The measured signal $m(t)$ is divided into two parts, one is the real signal $f(t)$, the other is the noise signal σZ_i .

$$m(t) = f(t) + \sigma Z_i \quad (2)$$

(2) in the formula, σ is the noise intensity, and Z_i is the additive white noise.

Set $\hat{f}(t)$ to $m(t)$ signal after wavelet threshold denoising after signal processing, then the variance between $\hat{f}(t)$ and $f(t)$ for real signals:

$$\kappa(\hat{f}(t), f(t)) = \frac{\sum^n E\{\hat{f}(t) - f(t)\}^2}{n} \quad (3)$$

The main objective is to make wavelet variance of κ value as far as possible infinite small, $\hat{f}(t)$ value is closer to the true signal. $f(t)$, signal to noise due to the frequency and energy spectrum is relatively dispersed, so wavelet coefficient absolute value is small, and scattered in most of the wavelet coefficients, and signal in wavelet domain is concentrated in a limited number of coefficients, therefore, after wavelet decomposition,

the signal coefficients greater than the noise coefficient. Therefore, a proper threshold th to balance out. At present, the threshold is the hard threshold function and soft threshold function two (here detailed description), estimation by the soft threshold wavelet coefficient is smaller than the real coefficient, thus affecting the accuracy of wavelet reconstruction. But because of the hard threshold in the wavelet space is not continuous, thus limiting the scope of application, this paper set up a new threshold function:

$$\eta(x, th) = \begin{cases} x - \frac{th^m * k}{x^{m-1}} + (k-1) * th & x > th \\ \frac{k * |x|^n}{th^{n-1}} * \text{sign}(x) & -th \leq x \leq th \\ x - \frac{th^m * k}{x^{m-1}} + (k-1) * th & x < -th \end{cases} \quad (4)$$

Wherein, m, n, k threshold function as regulatory factors, between (0,1) to set a value of k can overcome discontinuities and software functions hard threshold function decomposition in the wavelet coefficients when the existence of bias, and retain their advantages. Using the formula (4) to obtain the RSSI value for noise reduction processing, get the following formula (5)

$$m(RSSI_i) = f(RSSI_i) + \sigma \eta(RSSI_i, th) \quad (5)$$

s.t.

$$\sigma = \frac{\sum_{i=1}^n RSSI_i}{n-1}$$

The formula (5) can be optimized after the RSSI value, reduce the noise caused by the impact and subsequent using particle swarm algorithm provides the basis.

3. Particle Swarm Optimization

Particle Swarm Optimization (PSO) algorithm simulation group foraging behavior of birds flying in D -dimensional search space, position of the i particles ($i = 1, 2, \dots, m$) of $\mathbf{Z}_i = (z_{i1}, z_{i2}, \dots, z_{iD})$, $\mathbf{V}_i = (v_{i1}, v_{i2}, \dots, v_{iD})$ location i particle moving distance, $\mathbf{P}_i = (p_{i1}, p_{i2}, \dots, p_{iD})$ denotes a i particle "fly" in the best position history, $\mathbf{P}_g = (p_{g1}, p_{i2}, \dots, p_{iD})$ represents the population best position particle velocity and position update the following formula based on:

$$v_{id}(t+1) = \omega \times v_{id}(t) + c_1 \times \text{rand}() \times (p_{id}(t) - z_{id}(t)) + c_2 \times \text{rand}() \times (p_{gd}(t) - z_{id}(t)) \quad (6)$$

$$z_{id}(t+1) = z_{id}(t) + v_{id}(t+1) \quad (7)$$

Among them, t said the number of iterations; $C1, C2$ (rand) as the learning factor; is a random number between $[0, 1]$; ω is the inertia weight. Because the search performance of the inertia weight ω algorithm, this paper adopts linear inertia weight changes, in particular:

$$\omega = \omega_{\max} - t \times \frac{\omega_{\max} - \omega_{\min}}{t_{\max}} \quad (8)$$

Among them, ω_{\max} is the initial weight; ω_{\min} final weight; t_{\max} is the maximum

number of iterations for the current iteration; t is the current iteration number. When the maximum number of iterations or meet other iterative conditions, get the global optimal solution and the optimal position.

4. Weighted RFID Location

4.1 Weighting

RFID and WSN node localization has certain similarities, so the use of particle swarm algorithm to calculate the coordinates of the unknown label. The random initialization of N particles, each particle as a virtual reference tags, calculation of every particle of the value of RSSI. Assume the existence of K a reader, coordinate the estimated location of the undetermined tag t for (x_t, y_t) , which coordinates of the k a reader (x_k, y_k) , pending labels and reference RSSI values obtained according to the formula (1). When the signal intensity of the i a reader to read the positioning tags for the $RSSI_k$, through nonlinear difference calculated the i readers get the n particles signal strength for $RSSI_n$. In this paper, the signal intensity (RSS) is used as a weight value to locate the unknown tag. In Figure 1, for example, in a reference label N around the existence of different readers $\{A, B, C, D, \dots, K\}$, set the reader coordinates $A(x_A, y_A), B(x_B, y_B), C(x_C, y_C), \dots, K(x_K, y_K)$, therefore label N by way of reference to Table 1 record about the virtual tag reader node receives around issue path Distance and reader's node coordinate information RSSI signal strength, virtual tags and readers between.

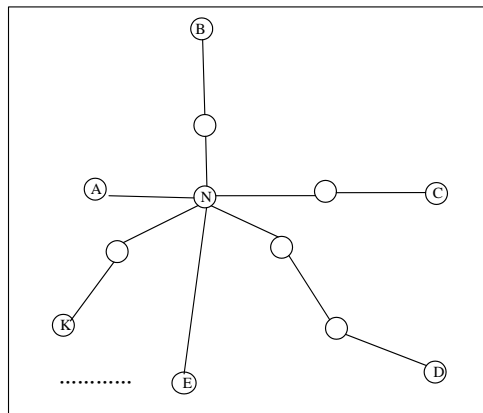


Figure1. Distribution of Virtual Label and Reader Examples

Table 1. RSSI Strength Value between Reader and Virtual Labels

Virtual label	RSSI Intensity	Virtual label and reader path distance	Reader coordinate
N→A	★★★★	36	x_A, y_A
N→B	★★★★★	40	x_B, y_B

N→C	★★★	52	x_C, y_C
.....
N→K	★	87	x_K, y_K

It can be found from the Table in the signal transmission distance is far, the RSSI value is weak, so the reader to tag virtual coordinates for solving the influence of relatively large, this article was considered from the above two factors, the specific numerical strength RSSI value comparison between the size and the RSSI value and size distance ratios as the reference coefficient by with the product of the coordinates of the reader to determine the coordinates of the virtual nodes. The calculations are as follows (9)

$$\left\{ \begin{array}{l} x_N = x_A * \frac{RSSI_{N \rightarrow A}}{S_{N \rightarrow A}} + x_B * \frac{RSSI_{N \rightarrow B}}{S_{N \rightarrow B}} + \\ \quad x_C * \frac{RSSI_{N \rightarrow C}}{S_{N \rightarrow C}} \dots\dots x_K * \frac{RSSI_{N \rightarrow K}}{S_{N \rightarrow K}} \\ y_N = y_A * \frac{RSSI_{N \rightarrow A}}{S_{N \rightarrow A}} + y_B * \frac{RSSI_{N \rightarrow B}}{S_{N \rightarrow B}} + \\ \quad y_C * \frac{RSSI_{N \rightarrow C}}{S_{N \rightarrow C}} \dots\dots y_K * \frac{RSSI_{N \rightarrow K}}{S_{N \rightarrow K}} \end{array} \right. \quad (9)$$

Among them, the $RSSI_{N \rightarrow R}$ says virtual tag to reader R between signal intensity and $S_{N \rightarrow R}$ said virtual tags to the path distance between readers.

The formula (9) calculation of all virtual label position as the particle swarm algorithm, followed by particle swarm optimization (PSO) algorithm to calculate the optimal virtual label position, which directly determine the position of reference tags to be.

4.2. Algorithm Flow

This paper calculates the coordinate of the label to be positioned according to the positioning algorithm based on the particle swarm and the algorithm process is as shown in Figure2

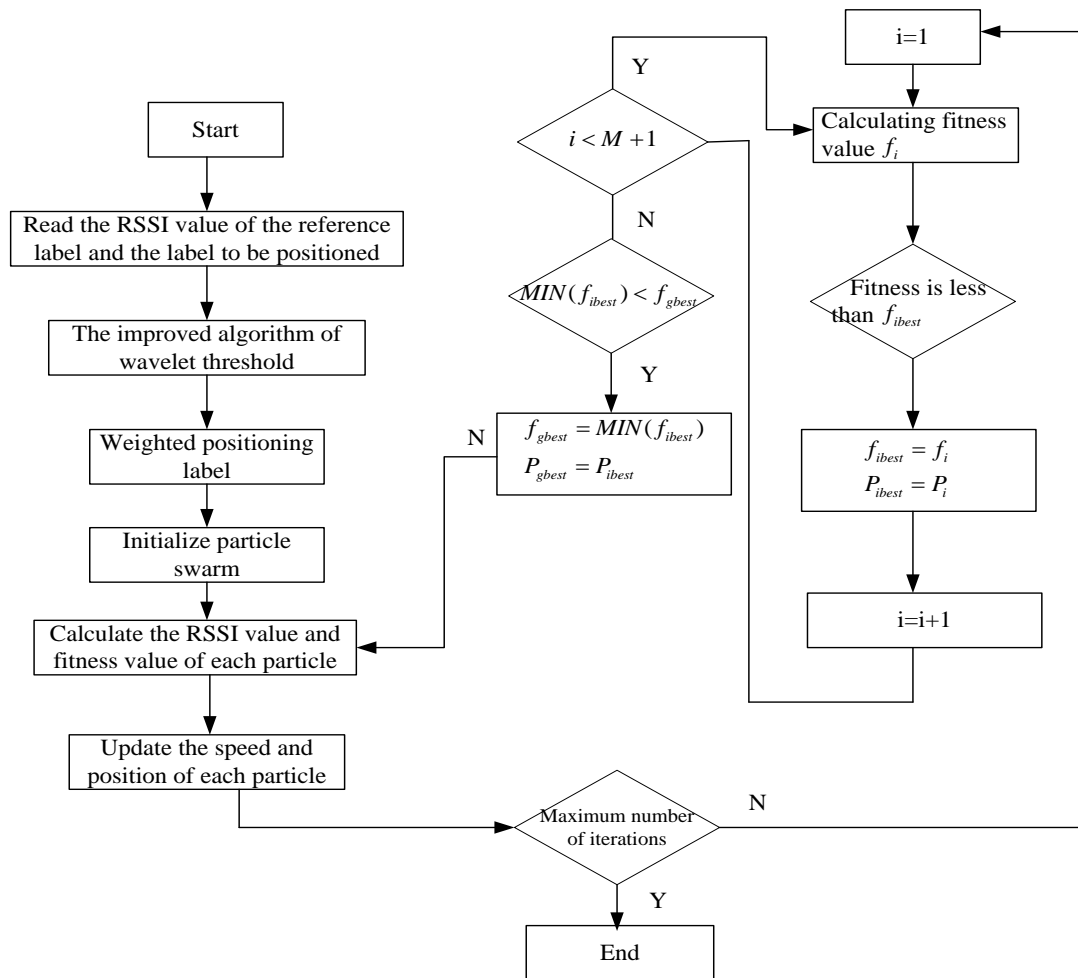


Figure 2. Algorithm Process

5. Experiment Simulation

In order to further test the superiority of the proposed algorithm in this paper, this paper sets the experimental environment according to Table 2 and generates 6 undetermined label coordinates at random as shown in Table 3.

Table 2. Experimental Environment

Experiment No.	Environment Space	Referential Coordinate Spacing	Referential Coordinate Amount	Amount of Readers
Experiment 1	10×10	2	20	10
Experiment 2	20×20	3	210	10
Experiment 3	30×30	2	701	10
Experiment 4	40×40	4	127	10

Table 3. Experimental Data

Experiment No.	Label No.	Abscissa	Y-axis
Experiment 1	1	2.07	3.12
	2	1.53	2.72
	3	4.82	3.15
	4	5.89	7.91
	5	7.81	9.72
	6	9.67	9.8
Experiment 2	1	11.72	17.89
	2	16.43	15.61
	3	18.98	19.31
	4	17.52	18.41
	5	15.61	16.89
	6	17.71	18.81
Experiment 3	1	10.12	23.89
	2	28.61	17.21
	3	19.72	27.41
	4	22.62	28.41
	5	26.61	28.13
	6	25.01	26.92
Experiment 4	1	20.61	34.71
	2	21.61	22.98
	3	32.87	33.81
	4	37.41	32.89
	5	35.81	39.23
	6	38.71	36.23

5.1. Comparison with Basic Positioning Algorithm

This paper compares VIRE [11] and SDQRI [2] aiming at the data of four experiments and the comparison results are as shown in Figure 3(a-d). It can be found from the figure that algorithm in this paper has less errors than the basic positioning algorithm in different experimental data, which is mainly because the weighting concept has been added in positioning to improve the positioning accuracy.

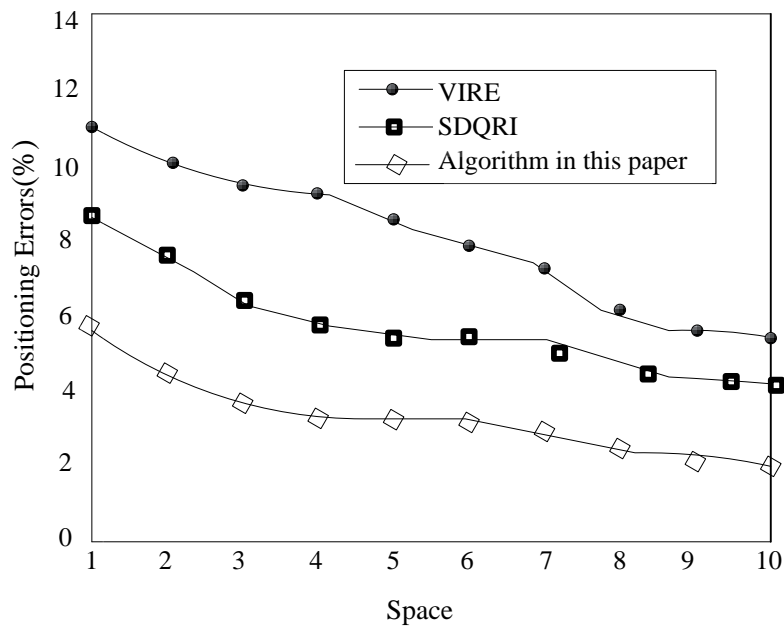


Figure3 (a). Results of Comparing Data of the First Experiment in Three Algorithms

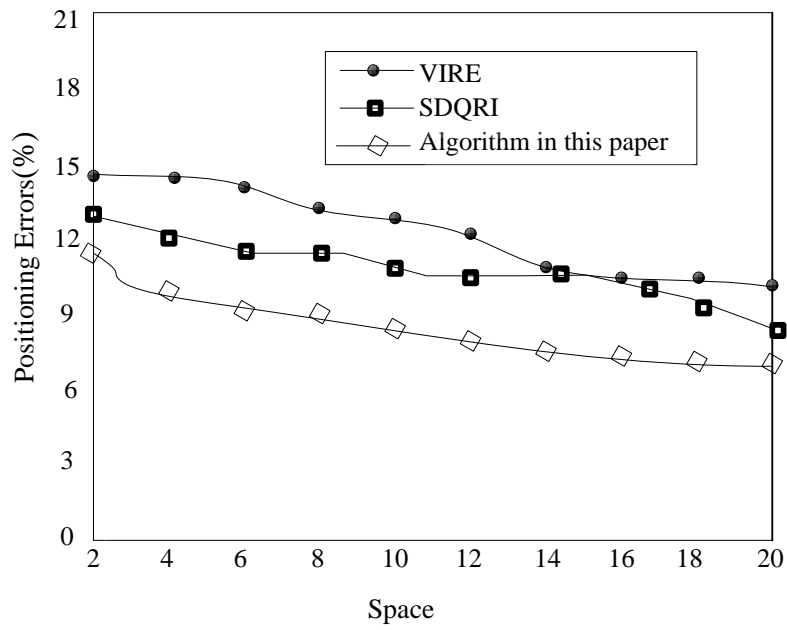


Figure 3 (b) Results of Comparing Data of the Second Experiment in Three Algorithms

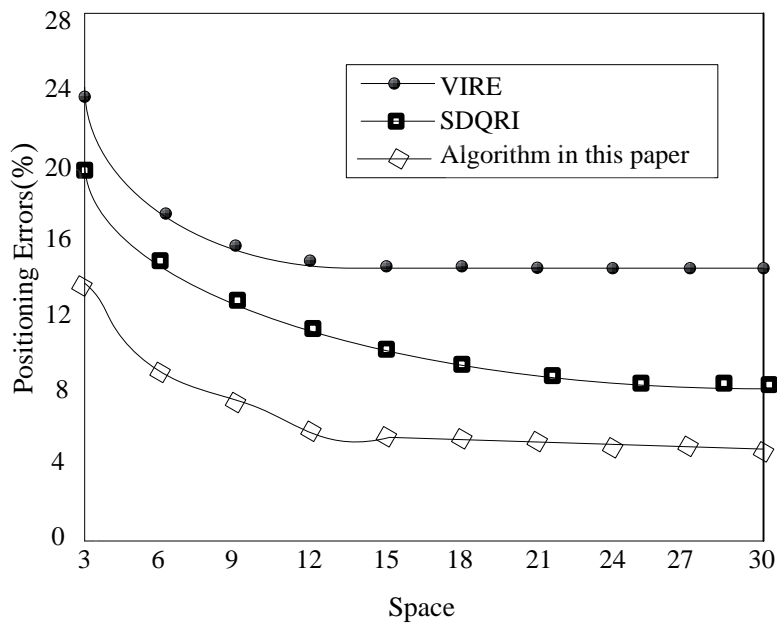


Figure 3(C). Results of Comparing Data of the Third Experiment in Three Algorithms

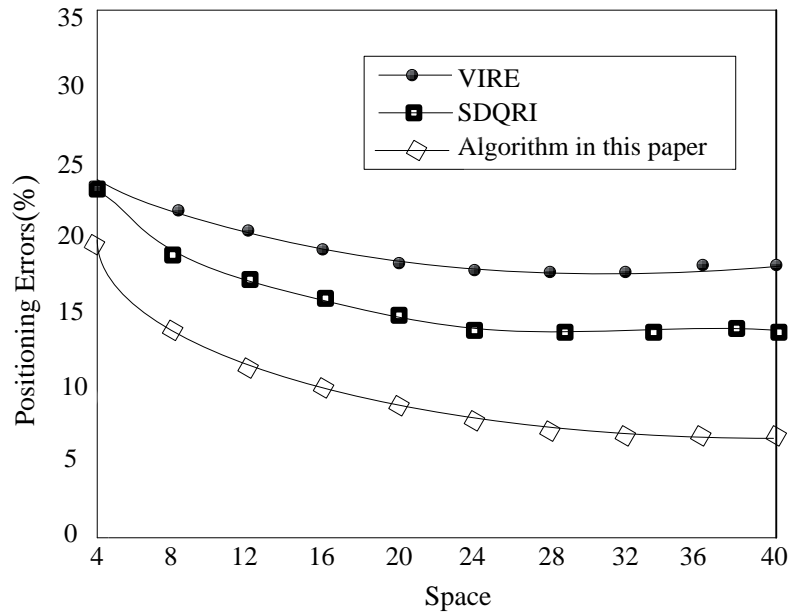


Figure 3(d). Results of Comparing Data of the Fourth Experiment in Three Algorithms

5.2. Comparison with Other Algorithms

Compare algorithm in this paper with literature [4] and [6] about this algorithm, and it can be found from the positioning errors and time consumed that the results are as shown in Figure4 and Figure5 It can be found from Figure 4(a-d) that algorithm in this paper has nearly 0 positioning errors, so it has good positioning effects.

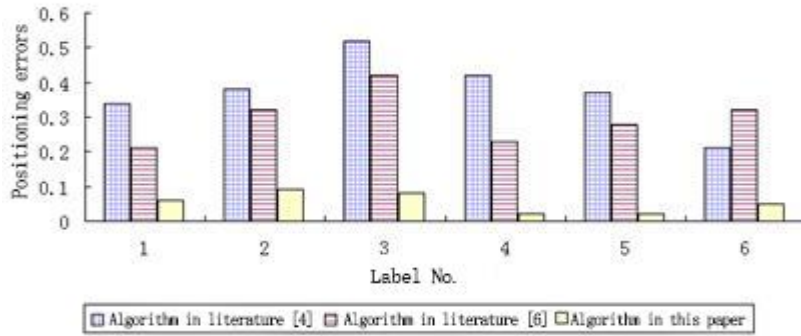


Figure 4 (a). Results of Comparing Data of the First Experiment in Three Algorithms

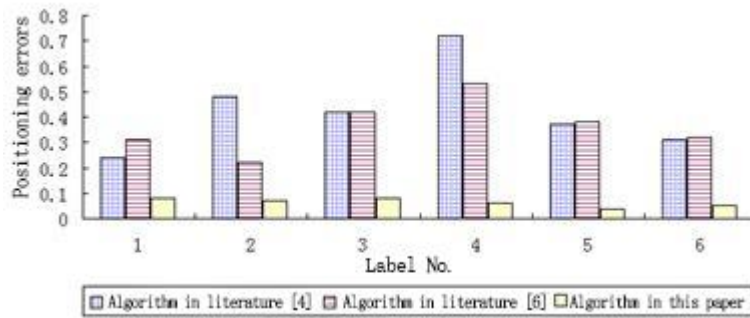


Figure 4 (b). Results of Comparing Data of the Second Experiment in Three Algorithms

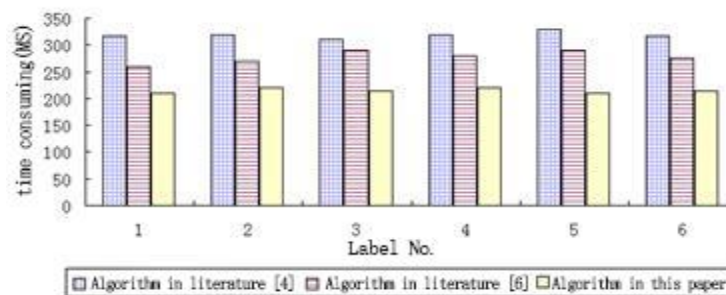


Figure 4 (c). Results of Comparing Data of the Third Experiment in Three Algorithms

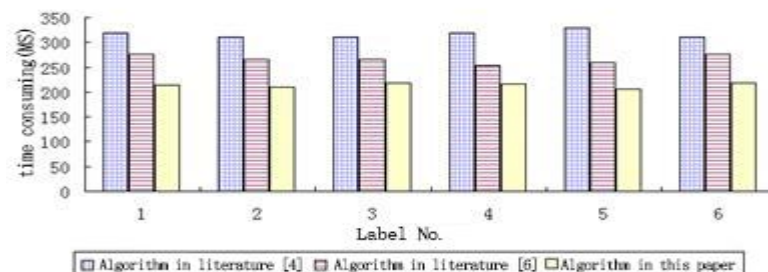


Figure4 (d). Results of Comparing Data of the Third Experiment in Three Algorithms

6. Conclusion

In the indoor positioning algorithm in this paper, aiming at the shortcomings of traditional VIRE algorithm, the RFID algorithm based on PSO algorithm has been proposed, and the virtual positioning label's accuracy has been improved by introducing the concept of weighting in positioning. The simulation experiments show that algorithm in this paper can effectively realize positioning accuracy to some extent, but how to improve positioning accuracy in a more complicated situation is the focus of future research.

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