An Advanced RFID Localization Algorithm Based on Region Division and Error Compensation

Junhuai Li, Guomou Zhang, Lei Yu, Zhixiao Wang and Jing Zhang
School of Computer Science and Engineering, Xi'an University of Technology
Xi'an, Shaanxi 710048 – P. R. China
[e-mail: lijunhuai@xaut.edu.cn]
*Corresponding author: Junhuai Li

Received January 5, 2013; revised April 3, 2013; accepted April 8, 2013; published April 30, 2013

Abstract

In RSSI-based RFID(Radio Frequency IDentification) indoor localization system, the signal path loss model of each sub-region is different from others in the whole localization area due to the influence of the multi-path phenomenon and other environmental factors. Therefore, this paper divides the localization area into many sub-regions and constructs separately the signal path loss model of each sub-region. Then an improved LANDMARC method is proposed. Firstly, the deployment principle of RFID readers and tags is presented for constructing localization sub-region. Secondly, the virtual reference tags are introduced to create a virtual signal strength space with RFID readers and real reference tags in every sub-region. Lastly, k nearest neighbor (KNN) algorithm is used to locate the target object and an error compensating algorithm is proposed for correcting localization result. The results in real application show that the new method enhances the positioning accuracy to 18.2% and reduces the time cost to 30% of the original LANDMARC method without additional tags and readers.

Keywords: RFID, Indoor location, Region division, LANDMARC, Error Compensation

This work was supported by a grant from the Natural Science Foundation of China (No. 61172018), the Science & Research Plan Project of Shaanxi Province (No. 2011NXC01-12) and Science & Research Plan Project of Shaanxi Province Department of Education (No.2010JC15, 12JK0737).

http://dx.doi.org/10.3837/tiis.2013.04.004

1. Introduction

Location awareness is becoming the most important issue in many fields in recent years, such as ubiquitous computing, mobile computing. There are many methods used to estimate locations such as GPS[1], ultrasonic, RFID[2-3], Wi-Fi and infrared [4], etc. They have been widely applied to various occasions according to the localization accuracy. The localization error ranges from several meters for the direction sensing[5] to several centimeters or even millimeters for the accurate localization[6]. Recently, with the popularity of Internet-of-Things[7], location awareness becomes a hot topic in the research area[8]. Among these localization technologies, RFID-based method is very popular for developers and researchers because of its advantages such as cost effectiveness and compactness. Many RFID-based localization methods are presented. LANDMARC[2] and VIRE[3] are two most well-known methods among them.

The location-sensing methods for RFID localization system include TOA(Time of Arrival)[9], TDOA(Time Difference of Arrival)[10], RSSI(Received Signal Strength Indication)[11-13], AOA(Angle Of Arrival)[14], and PDoA(Phase Difference of Arrival)[15], etc. Most of these methods suffer from high cost or the localization error problem which is caused by multi-path effect[16]. Therefore, they are not suitable for the low-cost indoor localization. Nevertheless the RSSI-based location-sensing methods are widely applied to various localization systems because of the ease of layout, the low-cost, and easy availability of RSSI. A typical example based on RSSI is LANDMARC. Reference tags were introduced to aid localization and reduce the number of readers, thus to reduce the cost. Meanwhile *k*-nearest neighbor algorithm was used to estimate the coordinates of the target tag. The localization accuracy was enhanced and the environmental adaptability was enabled.

There are many works to improve LANDMARC method. In literature [17], an improved method is proposed to reduce multi-path effect and enhance the localization accuracy by combining log-distance path loss model with Bayesian theory. Literature [18] firstly estimates the parameters of path loss model using the k-nearest neighbor tags, then calculates coordinates of target tag by using modified path loss model. Based on reference [18], an improved estimate method of path loss model parameters is presented to construct localization model, then this model is used to calculate coordinates of target object in literature [19]. In [20], different *k* values were used to locate the same nearest tags repeatedly, and the *k* value that corresponding to the smallest localization error was selected to estimate the location of the tracked tag. In [21], the key idea of the *k*-nearest neighbor algorithm was also utilized to locate the target object. In this method, *k* value is dynamically set and the self-correcting *k*-nearest neighbor algorithm is used according to the status whether reference tag work well or not. In [22], a pseudo-absolute localization algorithm based on the LANDMARC was proposed. It utilized the average error, which was obtained from the localization of the known neighbor tags, to modify the coordinates of the tracked tag. Literature [23] introduced an advanced LANDMARC with adaptive K-nearest algorithm. First, the nearest reference tag was found using the Euclidian distance, then original LANDMARC was used to located the nearest tag with different K. Next, the K value which has the lowest location estimation error was chosen as the best K to localize the target tag. In [24], an improved algorithm named Prior Measurement Error-correcting (PME) based on stationary readers was proposed. At first, figure out the location errors of several specified points close to the target tag and make records of them in advance. Then these errors can be approximately deemed as the location error of the target tag to modify the estimated coordinates calculated by LANDMARC. The algorithms mentioned in above works are proposed to improve the localization accuracy. However, the localization efficiency is not well considered by the proposed methods in those works.

As it is analyzed above, the key issue for LANDMARC method is to enhance the localization accuracy under the premise of reduction the computational time. In this paper, an advanced algorithm which improves the LANDMARC is proposed. The rest of this paper is organized as follows: section 2 introduces some basic algorithm and concepts briefly, and analyzes the key factors that affect the localization accuracy and efficiency deeply. Then a novel idea of region division, which is used to save the computational time and reduce the error because the redundant analyses and computations of the tags are avoided, is shown in section 3. Based on these, section 4 proposes a new mechanism, an error compensation method, to correct the localization error by the known location. In order to evaluate the performance of the proposed method, a lot of simulation experiments and the real application are shown in section 5. Finally, section 6 gives readers a conclusion of this paper.

2. Preliminaries

2.1 Related Background

2.1.1 Log-distance Path Loss Model

In order to predict received signal strength between RFID readers and tags clients, in this paper we employ the log-distance path loss model. In this model, average received signal power decreases logarithmically with distance in radio channels. Received signal power at a distance d from the transmitter is given by:

$$RSSI = RSSI_0 - 10n\lg(\frac{d}{d_0}) + \chi_\delta \quad (1)$$

Where d_0 denotes reference distance. $RSSI_0$ is the received signal strength value at distance d_0. d is the T-R(Transceiver-Receiver) separation distance in meters. $RSSI$ is the received signal strength value at distance d. n is path loss exponent, and it is related to the properties of the building material. X_σ denotes a Gaussian random variable with normal distribution N (0, σ^2).

2.1.2 LANDMARC Algorithm

Suppose there are n readers $R=\{R_1, R_2,\ldots,R_{n-1}, R_n\}$ in the localization area, m real reference tags $RT=\{RT_1, RT_2, \ldots, RT_m\}$, $RSSI=\{RSSI_{i1}, RSSI_{i2}, \ldots, RSSI_{im}\}$ is the signal strength vector between all reference tags and the i_{th} reader. Then the Euclidean distance E between the readers and the target tag RT_0 is calculated as:

$$E = \sqrt{\sum_{i=1}^{n}\left(RSSI_{i0} - RSSI_{ij}\right)^2} \quad (2)$$

where $RSSI_{i0}$ denotes RSSI value received by the i_{th} reader from tracking tag RT_0. $RSSI_{ij}$ is RSSI value received by the i_{th} reader from the j_{th} real reference tag. When the value of E is smaller, it means that the reference tag is closer to the target tag. By comparing the value of *E*, the *K* nearest neighbor reference tags are selected as a set of neighboring-tags *TopK*, the location of the target tag coordinate (*x*,*y*) is estimated as :

$$(x,y) = \sum_{RT_s \in TopK} w_s(x_s, y_s) \tag{3}$$

where (x_s, y_s) denotes the coordinate for tag RT_s. w_s is the weight factor corresponding to this tag. It is obtained by:

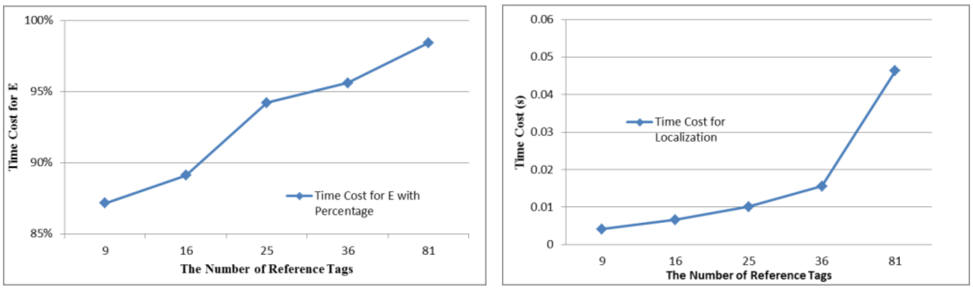
$$w_s = \frac{\frac{1}{E_s^{\,2}}}{\sum_{RT_s \in TopK} \frac{1}{E_s^{\,2}}} \tag{4}$$

2.2 Problem Analyses

2.2.1 Time Cost of Localization

In the LANDMARC algorithm and its improved algorithms, the calculation of Euclidean distance *E* is the essential step. However, the computation of *E* becomes quite complex and the time cost dramatically multiplies as the number of reference tags increase due to the requirements of localization accuracy and the expansion of the localization space.

A simulation result of the time cost for the computation of *E* along with the number of reference tags for LANDMARC algorithm is shown in **Fig. 1**. The time cost for the computation of *E* is represented by percentage accounted for the overall time cost. The localization space is 4.5m×4.5m.



(a) (b)

Fig. 1. Time Cost of LANDMARC

In **Fig. 1**, the time cost for localization rises dramatically from 0.0042 seconds to 0.047 seconds as the number of reference tags increases from 9 to 81. The percentage also increases from 87% to 98%. In other words, the computation of *E* turns into the overall cost for the localization process. Therefore, the reduction of the cost for computation of *E* under the premise of retaining the localization accuracy is the key issue for enhancing the performance of the algorithm.

2.2.2 Localization Accuracy

The localization accuracy is affected by many factors: the accuracy of devices, the layout, the inferences from the environment, etc.

(1)The selection of the nearest tags is influenced by the environmental interferences

It often happens that the real RSSI obtained by reader is quite different from the theoretical value of RSSI, and the real RSSI fluctuates under the influence of X_δ (shown in Eq.(1)). Moreover the error introduced by this fluctuation directly affects the accuracy of the E between the reference tag and the target tag. As a result, the selection of the nearest tag based on the value of E also deviates from the target tag. Therefore, the selection of the nearest tag based on the RSSI leads to low localization accuracy in this case.

It is known from the intensive simulation, it is not necessarily to consider the majority of the reference tags since they are far away from the target tag. So the time cost of the algorithm will decreases due to the reduction of number of the tags which is used to calculate the coordinate of target tag. Thus the stability of the algorithm and the localization accuracy is improved.

(2) LANDMARC lacks the localization error compensation mechanism.

In the LANDMARC algorithm, because the estimation of the target tag fully relies on the selected set of the nearest tags, there is no extra measure to deal with the introduced error by these selected tags. Only the weight value (shown in Eq.3-Eq.4) is involved for the final localization result.

Based on the above analyses, the idea of region division is introduced to restrain the selection of k neighbors by filtering the redundant data and devices in this paper. Furthermore, by combining with the error compensation method, the localization error of the target tag is corrected by the estimation of known location.

3. Layout of The Localization Space

3.1 Region Division

Based on the analysis of LANDMARC algorithm, the improvement of this algorithm should include both the efficiency and accuracy. In this paper, the idea of region division is introduced to reduce the computational time, and to enhance the accuracy and stability of the algorithm. Here are some concepts which will be used in the following part:

Definition 1, reference position: In the localization space, the reference position is the coordinates of the reference tags, which are used to aid the localization and their coordinates are known.

Definition 2, target position: In the localization space, the target position is the coordinates of locations of those tags which are to be estimated and their coordinates are not known.

Definition 3, the distinguishability of region: Each target position in this region has a sequence of readers ID which is sorted by the RSSI, and this sequence is never the same as other target locations' which are not in this region. In **Fig. 2(d)**, there are two test locations T_1 and T_2 in the region. According to the layout of the test locations and readers, these test locations aren't located in the same region but have the same one sequence of readers ID (R_1, R_2, R_3, R_4), which is sorted descendingly by the RSSI between the each location and all readers in theory. So the regions S_1 and S_2 are not of distinguishability.

Whether the region is distinguishable or not depends on the method of division, so as an important section, how to get a good division of the regions is related to the following factors: the layout of the readers, the size and the shape of sub-region, etc. The three rules are supposed to be followed.

Rule 1: Keep the distinguishability of region division

The division of the region is closely related to location environment and layout of readers. The division should be of distinguishability, namely, the divided sub-regions should be independent from each other. There is no superposition among them. If there is superposition among the sub-regions, and the target location is in one of the superposed sub-region, then the algorithm can't determine which sub-region the target tag is in. Take an example which has been shown in the simulation (**Fig. 2**). The localization space is in square shape, and 4 readers are in each of the vertexes, as shown in **Fig. 2**.

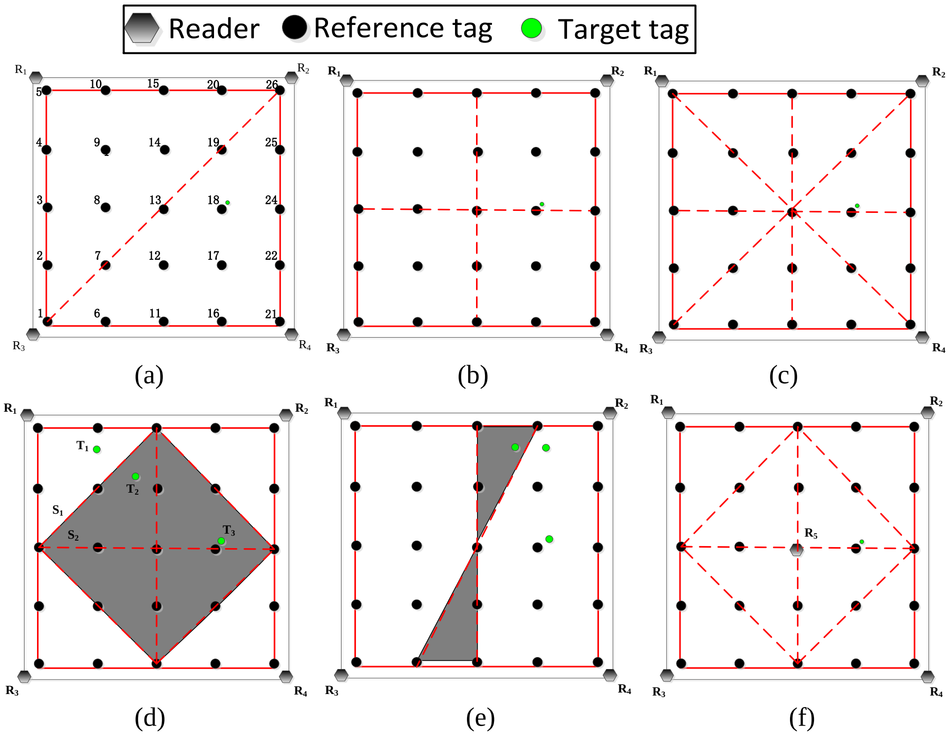


Fig. 2. Different Method of Division

In **Fig. 2**(a)-**Fig. 2**(e), there are 5 different division styles. The divisions in (a), (b), and (c) are of distinguishability. However, in (d) and (e), the target locations can't be distinguished in shadow area, in other words, the divisions in (d) and (e) are not of distinguishability.

Besides the application environment, the layout of the readers also influences the division. Diversified layouts of the reader and different number of readers make dissimilar divisions. For instance, in **Fig. 2**(f), reader R_5 is added into the layout shown in **Fig. 2**(e), which makes the layout be of distinguishability compared with **Fig. 2**(e).

To stress the importance of sub-region division and give readers some guidance and proof to implement this algorithm, a few theorems are shown below.

Theorem 1: The RSSI between the target location and the reader indicates the real distance between them. Thus the distinguishability of the RSSI for a sub-region equals the distinguishability of the real distance. In other words, the divisions are in fact determined by the real distance between the target location and the reader.

Proof is shown below.

It is known from Eq.1 that the RSSI value is a decreasing function of distance d. Then d is expressed as :

$$d = 10^{\frac{RSSI_0 - RSSI + \chi_\delta}{10^* n}} \times d_0 \tag{5}$$

In Eq.5, All the variables can be obtained from the application environment except RSSI. When the distance *d* changes, the value of RSSI also varies. Therefore, the value of RSSI can be determined by distance *d*.

Q.E.D.

Rule 2: Keep the division with right granularity

The area of the sub-regions should be suitable. The area of the sub-regions directly related to the complexity of the algorithm and the localization accuracy. If the granularity is too large, the improved algorithm has the same time cost and localization accuracy with the original algorithm. On the contrary, if too small, the time cost becomes high and the localization accuracy falls. In our experiment, we take an example using the square localization space (4.5m×4.5m). The interval between each reference location is 1 m. Suppose that the target location is at p(0.6,0.7). **Fig. 3**(a) and (b) shows the left lower corner of the division in **Fig. 2**(b) and (c) respectively.

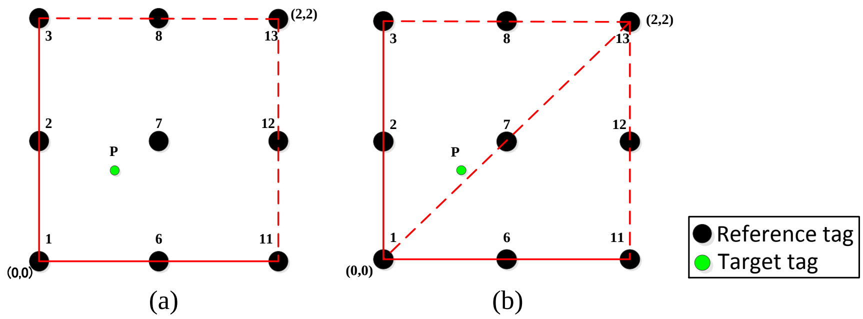


Fig. 3. Different Method of Division (Partial)

In the simulation, the algorithm to localize the target tag **P** runs 1000 times. When the localization space is divided as **Fig. 3**(a) and (b) respectively and *K=4*, the accuracy is shown in following **Fig. 4**.

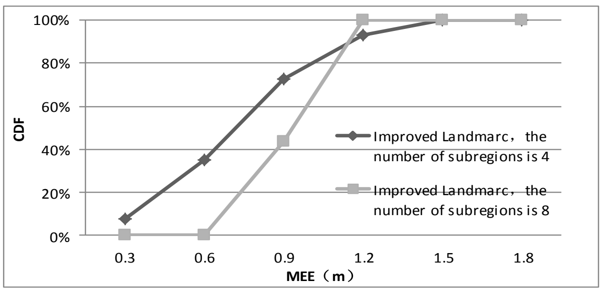


Fig. 4. Accuracy Comparison between 2 Methods of Division

In the **Fig. 4**, there are two kinds of granularity in division. When the number of sub-region is 4, which is divided as **Fig. 3**(a), the average of error is 0.73m, however, with the granularity increasing to 8,which is divided as **Fig. 3**(b), the average of error increases by 0.18m. So the different granularity make different accuracy, the division with right granularity can improve the accuracy.

Rule 3: Keep the division in regular shape according to the reference locations

Generally, the division can be a variety of shapes. Nevertheless, there is advantage to divide the location space into regular shapes. It reduces the complexity since the determination of the sub-regions becomes easier. Because the neighboring sub-regions are differentiated by the boundary between them, the computation of such boundary turns into significant. For example, for one square sub-region which is in regular shape, only the side length and the coordinate of one of its vertex are required to obtain all the its boundaries.

Furthermore, the specific shape of the division should be also based on the topologic structure of the reference locations; otherwise the localization accuracy may degrade.

This simulation brings in two solutions to layout the reference tags, and utilizes the method of division in **Fig. 2**(b) to divide sub-regions, the rest of environmental factors is the same as the section 3.1.The details are shown in **Fig. 5**.

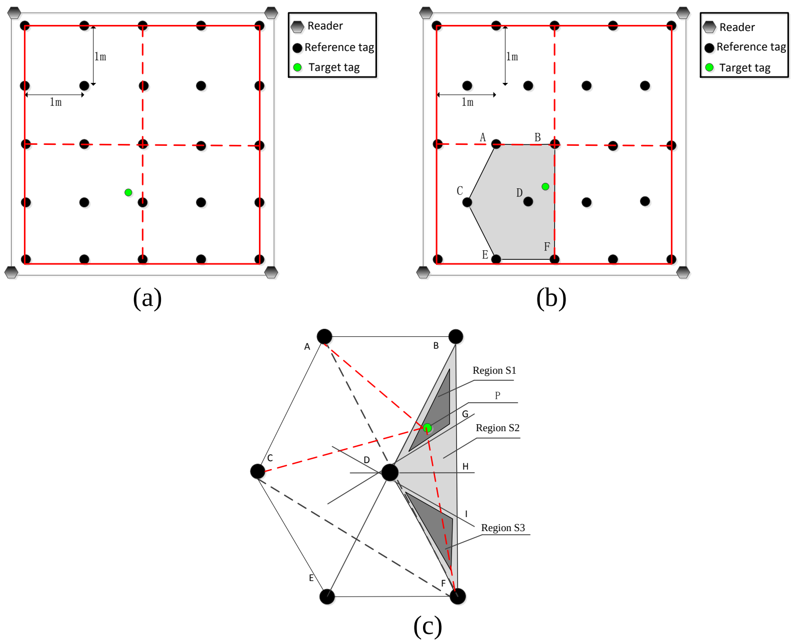


Fig. 5. Square and Isosceles-triangle Topologic Structure

There are two typical topologic structures of the reference locations as shown in **Fig. 5** (a) and (b): square topologic structure and isosceles-triangle topologic structure. The localization accuracy is higher when using isosceles-triangle topologic structure-based LANDMARC algorithm without region division[25]. However, when the same region division is used on these two typical topologic structures, the localization accuracy varies.

Fig. 5 (c) is the zoomed vision of the shading region in **Fig. 5** (b). The shading region S_2 is surrounded by edge tag *B*, *D*, *F* and the region boundary. Region S_1 which is surrounded by line *EB* and *DG* is one part of S_2. Line *EB* and *DG* are the perpendicular bisectors of line *CF* and *AF* respectively. Suppose that the target position ***P*** is in region S_1. According to the knowledge of geometry, ***P*** is close to tag *B* and tag *D* when the number of neighboring tags *K* =3. Then the candidates for the third neighboring tag are tag *A* and tag *F*. Since ***P*** is above the line *DG* which is the perpendicular bisector of line *AF*, tag *A* is selected from those two candidates. However, such selection leads to large localization error. The selected tag *B*, *D* and *A* together form a localization region. This region totally excludes the target position ***P***. Obviously this is a fatal error for the nearest neighbor-based localization algorithms. When the number of neighboring tag K =4, $\boldsymbol{P}$ is close to tag A, B, and D. And region S_2 is below line AF. Then the fourth tag is selected as tag F. The localization region turns into triangle $ADFB$. From **Fig. 5** (c), it is obviously that the selected neighboring tags are not suitable for the estimation of the localization result. The quantitative analyses are shown as follows.

In **Fig. 5** (c), it is obviously that the nearest reference tag which is close to the target position $\boldsymbol{P}$ is tag D. Then the selection of the remaining neighboring tags is discussed.

I. When K=3, there are two problems. ①For tag B, the length of PB, PA and PF should be compared; ②For tag A, the length of PA, PC and PF should be compared.

(1) Set the lower right corner as the origin of coordinates, and the horizontal interval between the tags is a, the vertical interval between the tags is b. Let line DH be the perpendicular bisector of line BF. Then the equation of line DH is:

$$y = b \tag{6}$$

And the coordinates for D and H are (a, b) and ($1.5a$, b) respectively. Because the target position $\boldsymbol{P}$ is above line DH, then we have:

$$PA < PF \tag{6.1}$$

Similarly, because the target position $\boldsymbol{P}$ is to the right of the perpendicular bisector of line AB, then we have:

$$PA > PB \tag{6.2}$$

Then from Eq.(6.1) and Eq.(6.2), it is known that tag B should be selected as the 2nd neighboring tag.

(2) From the geometric symmetry, it is known that the target position $\boldsymbol{P}$ is below the line BE which is the perpendicular bisector of line CF. Then we have:

$$PC > PF \tag{6.3}$$

Let line DG be the perpendicular bisector of line AF, and its equation is:

$$\frac{y-b}{x-a} = \frac{a}{2b} \tag{7}$$

And the coordinates for D and G are (a, b), and ($1.5a$, $b+a^2/4b$) respectively. Because the target position $\boldsymbol{P}$ is above line DG, then we have:

$$PA < PF \tag{6.4}$$

Then from Eq.(6.3) and Eq.(6.4), it is known that tag A should be selected as the 3rd neighboring tag.

II. When K=4, the selection of the former three neighboring tags is the same as that case when K=3. The selection of the 4th neighboring tag should consider the length of PC and PF. Let line BE be the perpendicular bisector of line CF, and its equation is:

$$\frac{y}{2x-a}=\frac{b}{a} \tag{8}$$

And the coordinates for *B* and *E* are (*1.5a*, *2b*), and (*0.5a*, *0*) respectively. From the geometric symmetry, it is known that the target position ***P*** is above the line *BE* which is the perpendicular bisector of line *CF*. Therefore, the 4^{th} neighboring tag is selected as tag *F*.

From the selection process of the neighboring tags, no matter when K=3 or K=4, it is known that the selection of the neighboring tags has a low accuracy for the localization based on isosceles triangle topologic structure. The simulation results of the localization based on the two topologic structures are shown in **Fig. 6**. The target positions for the localization are selected from the five positions on the sub-region edge.

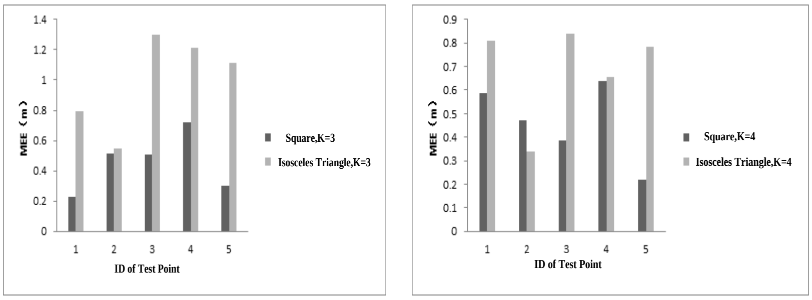


Fig. 6. Accuracy Comparison between Different Topologic Structures in Sub-region Edge

It indicates that the localization accuracy based on square topologic structure is higher than that isosceles triangle topologic structure in **Fig. 6**. The difference of this accuracy is as high as 0.6m. Therefore, the layout of the reference locations directly influences the division of the regions. It is a significant factor for the region division-based localization algorithm.

3.2 The Layout of The Readers

Definition 4, the recursion characteristics of the region division: the region can be divided into many sub-regions which are similar to the original region and keep the distinguishability.

The layout of the readers is closely related to the localization space, and it also influences the division of the regions. For the regular localization space, The reading areas of all readers should cover the overall localization space and be spaced regularly. It is shown in **Fig. 7** (a), the localization region is a regular shape and consists of the four sub-regions S_1, S_2, S_3 and S_4, which are divided by the five readers easily.

The above mentioned region division method is based on the positions of reference tags and the layout of the readers. While in the non-regular shape-based localization space, it is better firstly to determine the shape of the sub-regions according to the layout of the reference tags and the characteristics of the region. Then to cover the overall region using geometric style, and finally to arrange the readers based on the results of the region division. This division for non-regular shape is shown in **Fig. 7**(b),the four sub-regions S_1, S_2, S_3 and S_4 which aren't of same size can cover the whole localization space by five readers only. Therefore, the shape of the sub-region which is used to cover the overall region has large influences to the accuracy and efficiency of the localization algorithm. In this paper, the intensive experiments indicate that when the shape of the sub-region is isosceles right triangle or square, the localization result is better. The reasons are as follows.

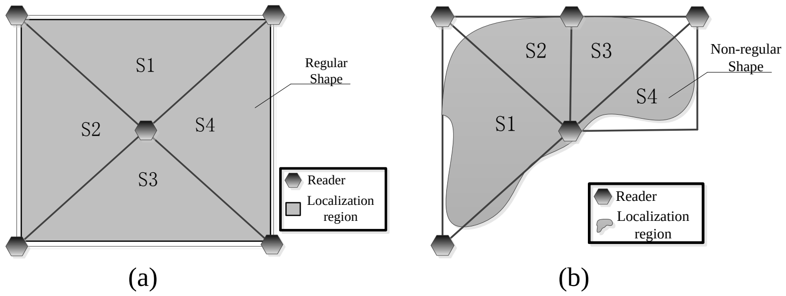


Fig. 7. Regular and Non-regular Shape-based Localization Space

(1) It is easy to obtain the layout of all readers since the isosceles right triangle or square has some characteristics, such as geometric symmetry and perpendicular bisector, etc. Therefore, the coordinates of the readers are also easily obtained based on these shapes. An example of the isosceles right triangle is shown in **Fig. 7**. In **Fig. 7** (b), the localization space is roughly divided into four sub-regions which are in isosceles right triangle shape. Only three readers per sub-region are sufficient to determine which sub-region the target tag is in.

(2) The region division is recursive and all of the sub-regions obtained by recursive division are distinguishable.

As shown in **Fig. 8**(a), if the reading area of three readers can not cover the overall region, then one more reader can be added, which divides the localization space into two parts. And the obtained sub-regions still keep the distinguishability. If the higher accuracy is required, the sub-regions need to be divided into some smaller regions continually.

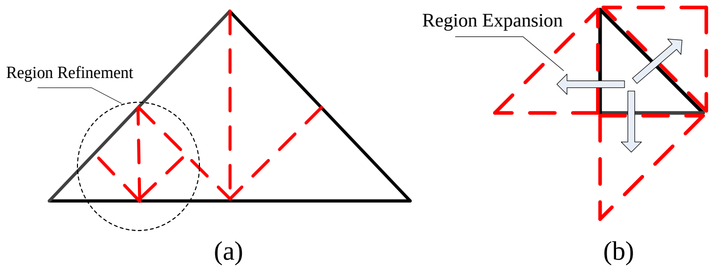


Fig. 8. Region Expansion and Refinement

Theorem 2: For the covering to the overall region based on isosceles right triangle, the edge coordinates of the new obtained region can be computed according to the coordinates of the original region no matter this region is obtained by region expansion or region refinement.

Proof:

In the localization space, suppose the coordinates of the three vertexes of the isosceles right triangle are known. The region is expanded from the three sides of the isosceles right triangle. The coordinates of the expanded isosceles right triangles can be easily computed since the region expansion is based on the geometric position. On the other hand, for the region refinement, since the refinement is from the inside of the isosceles right triangle, the coordinates of obtained isosceles right triangles which are in fine granularity can be computed by the geometric symmetry. Thus no matter it is obtained by region expansion or region refinement, the coordinates of the new obtained region can be computed and exclusively determined according to the coordinates of the original region. The result is shown in **Fig. 8**.

Q.E.D.

4. The Error Compensation method

4.1 The Compensation Method

Because there exists some unexpected interferences in the localization environment, the RSSI fluctuates sharply, which leads to the inaccurate estimation of the distance from reference tag to reader. In most state-of-the-art researches, the filtering method of RSSI is used to enhance the localization accuracy [26]. However, they will increases the localization time On the other hand, the conventional localization algorithms with error compensation mainly apply the co-correction of neighboring tags or verification of the estimation value to the original localization equation [27, 28]. However, the estimation error of the known positions can't represent the estimation error for those unknown positions precisely, which leads to low localization accuracy.

Based on the above analyses, we propose an error compensation method enhance the localization accuracy without using filter algorithm. In the proposed algorithm, we respectively estimate the positions of the target tag and the reference tag which is the nearest one to the target tag by using *k-NN* method. Since the coordinates of the nearest reference tag are known, the estimation error can be computed. Then this error value is used to correct the coordinates of the estimated target location. The error compensation process is shown in **Fig.9**.

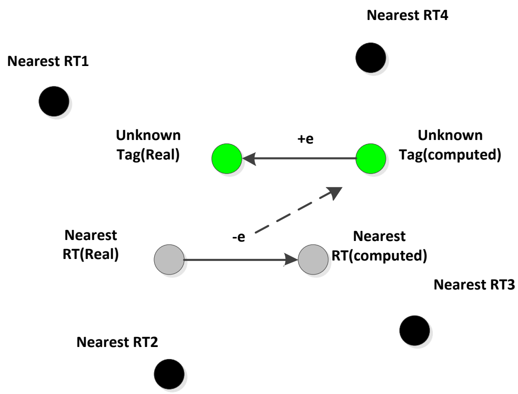


Fig. 9. Error Compensation (K=4)

The theoretical analysis is as follows.

Suppose there are *m* reference tags, *n* readers, and one target tag *T*. The coordinate of *T* is (x_0, y_0). The number of neighbor reference tags is *K* ($3<=K<=m$). The set of the neighbor reference tags is *NRT*, and the nearest reference tag $KEYRT(x_k, y_k)$ is not included. Let the Euclidean distance from *K* neighbor reference tags to the target tag *T* be E_1, $E_2 ... E_j$, where $j=1, 2, 3…K$.

The weight values of *k* neighbor reference tags are calculated using E_j. The coordinates of the target tag *T* are estimated as (x', y') and the estimation error is as:

$$(x_e, y_e) = (x' - x_0, y' - y_0) \tag{9}$$

Similarly, the coordinates of the nearest reference tag *KEYRT* is also estimated. Suppose the Euclidean distances from *K* reference tags to *KEYRT* are $E_1+\Delta_1$, $E_2+\Delta_2 … E_j+\Delta_j$ respectively, where E_j is the Euclidean distances from the j_{th} neighbor reference tag to the target tag *T*, Δ_j is the differential Euclidean distances between E_j and the Euclidean distance which is from the j_{th} neighbor reference tag to *KEYRT*. And $j=1, 2, 3…K$. The weigh value is computed by:

$$w_j' = \frac{\frac{1}{(E_j + \Delta_j)^2}}{\sum_{j=1}^{K} \frac{1}{(E_j + \Delta_j)^2}} \tag{10}$$

where W_j' is the weight value of j_{th} neighbor reference tag to the *KEYRT*. From Eq.10, the coordinates of *KEYRT* is estimated as (x'_K, y'_K), the estimated error is as:

$$(x_{Ke}, y_{Ke}) = (x'_K - x_K, y'_K - y_K); \tag{11}$$

The relation between x_e-x_{Ke}, y_e-y_{Ke} and Δ_j is computed as:

$$\begin{aligned} x_e - x_{Ke} &= x' - x'_K - (x_0 - x_K) \\ &= \sum_{i=1}^{K} x_i \times \left(\frac{\frac{1}{E_i^2}}{\sum_{j=1}^{K} \frac{1}{E_j^2}} - \frac{\frac{1}{(E_i + \Delta_i)^2}}{\sum_{j=1}^{K} \frac{1}{(E_j + \Delta_j)^2}} \right) - (x_0 - x_K) \end{aligned} \tag{12}$$

where Δ_{Ei} is

$$\Delta_{Ei} = \frac{\frac{1}{E_i^2}}{\sum_{j=1}^{K} \frac{1}{E_j^2}} - \frac{\frac{1}{(E_i + \Delta_i)^2}}{\sum_{j=1}^{K} \frac{1}{(E_j + \Delta_j)^2}}; \tag{13}$$

Thus, we have

$$x_e - x_{Ke} = \sum_{i=1}^{K} x_i \times \Delta_{Ei} - (x_0 - x_K);$$

When the distance between *KEYRT* and *T* decreases, the value of Δ_i tends to 0. Then we have

$$\lim_{\Delta_i \to 0} (X_0 - X_K) = \lim_{\Delta_i \to 0} (\Delta_{Ei}) = 0 \tag{14}$$

Furthermore, because that when *KEYRT* is close to *T*, the estimation errors are equal, expressed as:

$$\lim_{KEYRT \to T} (x_e - x_{Ke}) = 0 \tag{15}$$

Similarly, the following equation can be derived.

$$\lim_{KEYRT \to T}(y_e - y_{Ke}) = 0 \tag{16}$$

4.2 The Localization Error Compensation Algorithm

Based on the above analysis, it is known that the localization errors are more similar when the nearest reference tag is closer to the target tag during the localization processes that both the target tag and its nearest reference tags using same *k* neighboring tags respectively.

By the introduction of region division and localization accuracy compensation, both the accuracy and efficiency of the improved LANDMARC algorithm are enhanced. The steps of the algorithm are summarized in detail as follows

(1) To obtain the RSSI of the target tag *T* from all the readers and sort on it;

(2) To determine the distance according to the sorting result in (1), and determine the sub-region *AR*;

(3) To search for the reference tags *RT* in the sub-region *AR*;

(4) To obtain the RSSI of *RT*, and compute the Euclidean distance *E* from target tag *T* to *RT*;

(5) To select the *K*+1 reference tags *NRT* which are the nearest to *T*;

(6) To select the reference tag *KEYRT* which is the nearest to the target tag, and estimate the coordinate of *KEYRT* by the other *K* neighboring reference tags;

(7) To compute the estimation error of *KEYRT* (x_e, y_e);

(8) To estimate the coordinate of the target tag *T* (x', y') by *K* neighboring reference tags which are in *NRT* but are not *KEYRT*;

(9) To compensate the estimated coordinates of *T* by the estimated error from KEYRT, namely, (x, y)= ($x'+x_e$, $y'+y_e$).

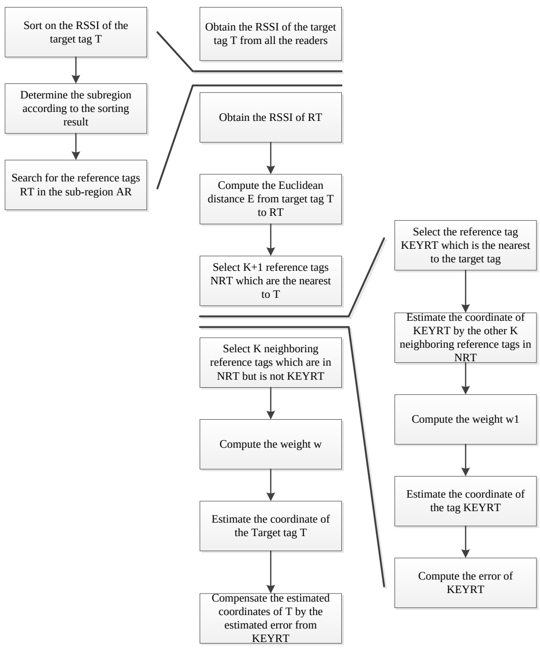


Fig. 10. Flow Chart

5. Experimental Results and Analysis

In order to evaluate the localization accuracy of the proposed algorithm, the Mean Estimation Error (MEE) is used as a metric. It is defined as:

$$MEE = \frac{1}{n}\sum_{i=1}^{n}\sqrt{\left(x-x_0\right)^2+\left(y-y_0\right)^2} \tag{17}$$

where (x_0, y_0) and (x, y) are the real coordinates and estimated coordinates of the target tag respectively, n denotes the localization times. Moreover, the time cost of the algorithm is used as another metric to evaluate the efficiency of the proposed algorithm.

5.1 Simulation Experiments

In the experiment, MATLAB is used for simulation. The localization space is in square shape with size 4.5m×4.5m, and it is in the reading area of 4 readers. There are 25 reference tags (m=25), and they are distributed based on the square topologic structure. The interval between reference tags is 1m, and the number of nearest tags is K=4. The layout of the tags is as that shown in **Fig. 5**(a). It is assumed that the number of sub-region is 4, and in square shape (the same as shown in **Fig. 5**(a)). In the simulation, the index for distance path loss of RSSI is set as N=3.45 dB and δ =5.2 dB.

5.1.1 Accuracy of Localization

Suppose that there are 21×21 target tags in the localization space. The LANDMARC algorithm, VIRE algorithm, Adaptive K-Nearest algorithm, WPME and the proposed algorithm (improved LANDMARC algorithm) are used to localize each target tag for 300 times. The Cumulative Distribution Function (CDF) is computed to compare the error distributions of the three algorithms. The results are shown in **Fig. 11**(a)-(d), which represent the localization results for the number of neighboring tags K=3 and K=4 respectively.

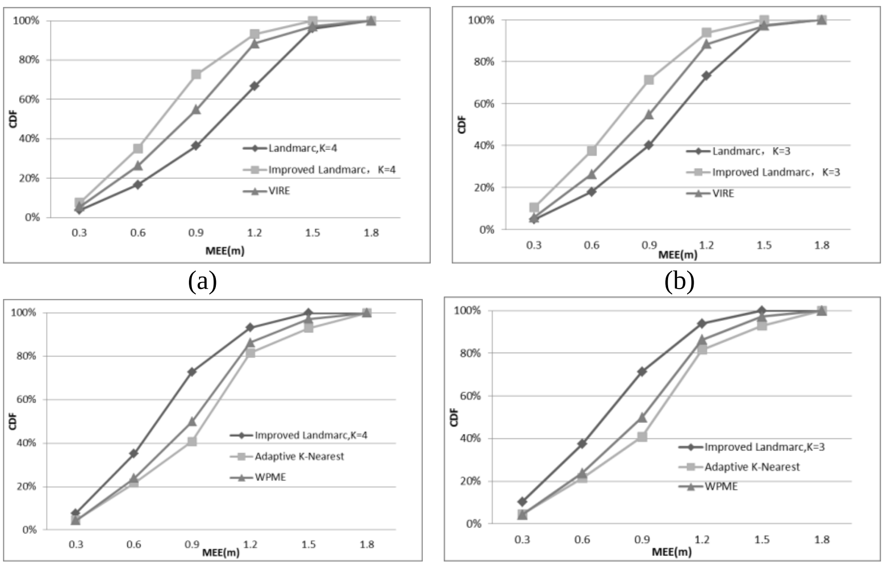


Fig. 11. Accuracy Comparison between Different Algorithms

In **Fig. 11**(a) and (b), although the localization accuracy of the virtual reference tag-based algorithm VIRE is higher than the LANDMARC algorithm, the improved LANDMARC has a remarkable higher localization accuracy compared with VIRE. When K=4, the average error of the improved LANDMARC is only 0.72 m, which is lower than the VIRE (average error is 0.87 m) by 17%, and it is lower than the LANDMARC algorithm (average error is 0.98 m) by 27%. Furthermore, when the LANDMARC is used for localization, the number of target tag of which the error is smaller than 0.9 m only accounts for 36.5% of the overall locations, while it accounts for 72.8% for the improved LANDMARC algorithm. This ratio is almost twice of the LANDMARC algorithm. In **Fig. 11**(c) and (d), Adaptive K-Nearest and WPME in accuracy are all still lower than the improved LANDMARC. The average error of Adaptive K-Nearest and WPME are 0.90m and 0.82m respectively, and higher than the improved algorithm (K=4) by 0.20m and 0.10m.

5.1.2 Localization Efficiency

Because the computation of Adaptive K-Nearest, WPME and VIRE algorithm are rather complex, the time cost for their localization is higher than that of LANDMARC algorithm obviously. Thus, the localization efficiency of LANDMARC algorithm and the improved LANDMARC is discussed in the following. The time cost of the LANDMARC algorithm mainly depends on the computation cost of E value. And as the number of reference location increases, the time cost of computation of E dramatically rises. The efficiency of both the LANDMARC algorithm and the improved LANDMARC algorithm along with the number of reference tags is shown in **Fig. 12**.

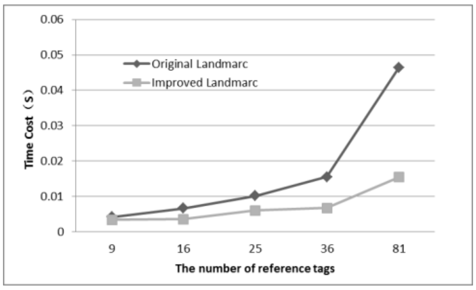


Fig. 12. Efficiency Comparison

In **Fig. 12**, as the number of reference tag increases, the time cost of the LANDMARC algorithm also rises higher than the improved LANDMARC algorithm. When the number of reference tag is 9×9, the time cost of the LANDMARC algorithm dramatically increases from 0.005 s to 0.047 s, which is nearly 10 times. By contrast, the time cost for the improved LANDMARC algorithm increases from 0.004 s to 0.015 s, which is only about 4 times, especially when the number of reference tags is 81, the efficiency of the improved method is 3 times higher than the original method. From the tendency of the time cost of the two algorithms, the improved LANDMARC algorithm is on a lower and stable rise curve compared with that of LANDMARC algorithm.

5.1.3 Performance Comparisons under Different Environment

The fluctuation of RSSI is mainly due to the interference of the environment. The X_σ in the log-distance path loss model represents the environment interference. It is a variable which has an $N(0, \sigma^2)$ distribution. Different value of σ represents the environment interference in different strength. The localization performances of the five algorithms (LANDMARC algorithm, VIRE algorithm, Adaptive K-Nearest, WPME and the improved LANDMARC algorithm) under different environment are analyzed in the following experiments. The result is shown in **Table 1**.

Table 1. Accuracy Comparison in Different Environment

Average error(m)	σ=0dB		σ=5.2dB		σ=8dB	
	K=3	K=4	K=3	K=4	K=3	K=4
Original LANDMARC	0.232	0.264	0.965	0.981	1.227	1.245
VIRE	0.210		0.87		1.113	
Adaptive K-Nearest (1<K<10)	0.221		0.90		1.19	
WPME	0.255		0.82		1.10	
Improved LANDMARC	0.225	0.247	0.716	0.721	0.964	0.951
Accuracy Enhancement	3%	6.4%	25.8%	26.5%	21.4%	23.6%

In **Table 1**, the performance of the improved LANDMARC algorithm is better than the other algorithm under different value of σ. When σ=5.2 dB, the improved LANDMARC algorithm has the largest accuracy enhancements: 25.8% and 26.5% for different K values compared with the LANDMARC algorithm.

5.2 Practical Application

5.2.1 Environment and Devices of Experiment

1. Experimental Environment

In order to validate the reliability of the proposed algorithm, a practical test is held in a corridor, which has a length of 65m and a width of 2m. A $2\times10m^2$ rectangular region is chosen as a localization area. This region is much more narrow and sheltered by two walls, so that multipath effect is more serious than other environment, but this region is in a stable environment, so other interference factors couldn't be considered. The region is shown in **Fig. 13**.

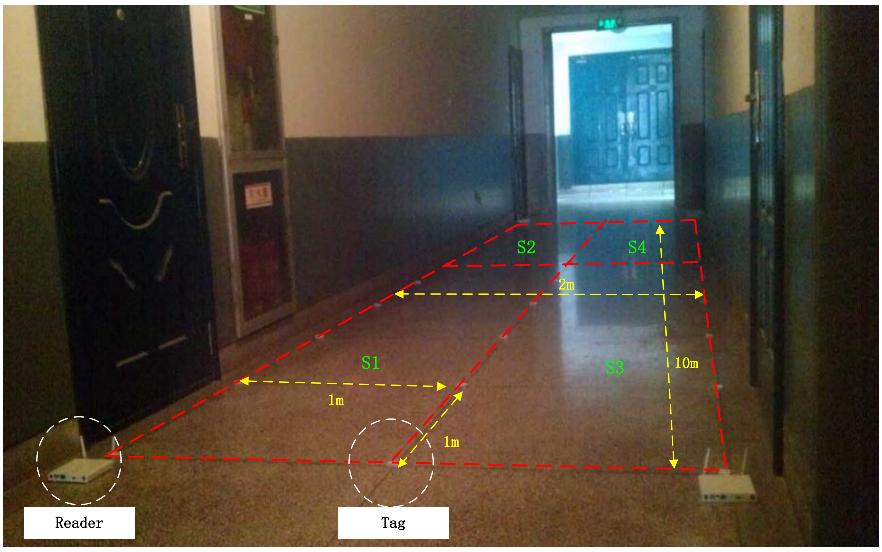


Fig. 13. Experimental Environment

2. Devices of experiment

This study uses RFID readers and active tags to construct the experimental environment. The devices (shown in **Fig. 14**) used in this test are all produced by RFCode Company. The parameters of these RFID devices are shown in **Table 2** and **Table 3** using the standard functions of the two kinds of devices.

Table 2. Parameters of Tag M100

Tag		M100	
Operating Frequency	433.92MHz	Typical Transmission Range	Up to 300 f
Group Code & Tag ID Codes	>540,000TagID per Group	Modulation	ASK

Table 3. Parameters of Reader M250

Reader		M250	
Operating Frequency	433.92MHz	Tag density	Up to 140 tag reports per second (TRPS)
Protocal	TCP/IP	Protocal	TCP/IP
Receiver sensitivity	> 50 dB dynamic range (-58 dB to -108 dB)	Default Range Settings	8 factory programmable range settings in 5 dB increments

(a) (b)

Fig. 14. RFID Reader and Tag

3. Layout of Readers and Tags

Based on the proposed theories, positioning region is arranged as **Fig. 15**. Because the area is a regular rectangle, it can be divided into four sub-regions S_1, S_2, S_3, S_4 by four readers directly, which are located in four vertices of rectangle respectively. Each sub-region is surrounded by 11 tags and has the distinguishability on RSSI, the interval between tags is 1m.

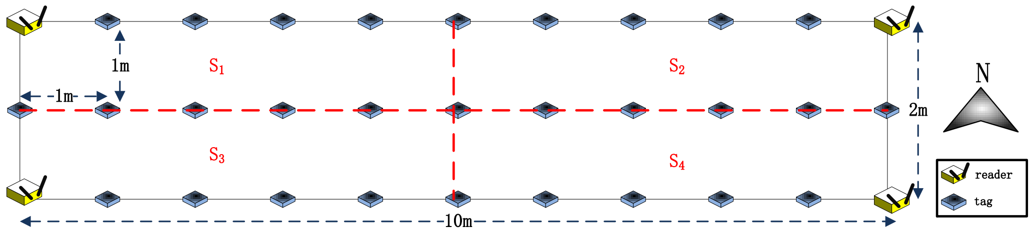
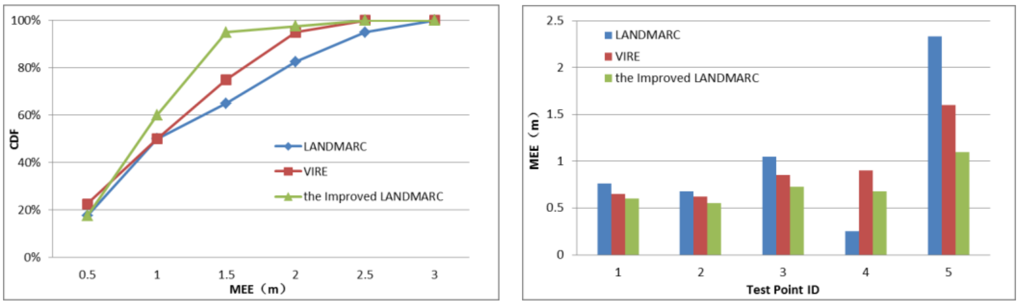


Fig. 15. Layout of Readers and Tags

5.2.2 Experimental results and analysis

In the positioning region, 40 test points are chosen as target tags, and the LANDMARC algorithm, VIRE algorithm, and the proposed algorithm (improved LANDMARC algorithm) are used to localize each target tag for 50 times. The Cumulative Distribution Function (CDF) is computed to compare the error distributions of the three algorithms. The results are shown in **Fig. 16** (a) and (b), which represent the localization results for the number of neighbor tags K=4.



(a) (b)

Fig. 16. Accuracy Comparison between Different Algorithms

In **Fig. 16** (a), the improved LANDMARC has a remarkable higher localization accuracy compared with original LANDMARC and VIRE. Although the localization accuracy of the virtual reference tag-based algorithm VIRE is higher than the LANDMARC algorithm, the average error of the improved LANDMARC is only 0.99 m, which is lower than the VIRE (average error is 1.11 m) by 10.8%, and it is lower than the LANDMARC algorithm (average error is 1.21 m) by 18.2%. Furthermore, when the LANDMARC is used for localization, the number of target tag of which the error is smaller than 1.5 m only accounts for 65% of the overall locations, and VIRE accounts for 76%, while it accounts for 95% for the improved LANDMARC algorithm. For verifying the validity of the error distribution, the errors of 5 target tags with different algorithms, which are chosen from 40 ones randomly, are shown in **Fig. 16** (b), these errors are highly consistent with the **Fig. 16** (a) except the forth point's, and the biggest drop of the error is 1.2m.

6. Conclusion

In this paper, the idea of region division is introduced for indoor localization. The selection, division, and layout of sub-region are analyzed in detail. Based on this key idea and combined with error compensation, an improved LANDMARC algorithm is proposed. The proposed algorithm avoids the analysis and computation of the redundant tags. Thus it saves time cost and reduces the error probability. Moreover, the compensation to the initial value of the target position using estimation error from known location enhances the both the efficiency and the accuracy. The result of simulation and real application indicates accuracy and efficiency of the proposed algorithm all have better performance than others. Especially in real application, the average error of the improved LANDMARC is only 0.99 m, which is lower than the VIRE (average error is 1.11 m) by 10.8% and the LANDMARC algorithm (average error is 1.21 m) by 18.2%, and its efficiency is increased to 3 times as compared with original algorithm.

References

[1] Barrios, C.,Y. Motai, "Improving Estimation of Vehicle's Trajectory Using the Latest Global Positioning System With Kalman Filtering," *Instrumentation and Measurement, IEEE Transactions on*, Vol.20,No.12,pp.3747-3755,2011.Article (CrossRef Link)

[2] Ni, L.M., Y. Liu,Y.C. Lau, "LANDMARC: indoor location sensing using active RFID". *Wireless Networks*, Vol.10,No.6,pp.701-710,2004. Article (CrossRef Link)

[3] Zhao, Yiyang, Yunhao Liu, and Lionel M. Ni, "VIRE: Active RFID-based localization using virtual reference elimination," *Parallel Processing, 2007. ICPP 2007. International Conference on. IEEE*, 2007.Article (CrossRef Link)

[4] Sanpechuda, T.,L. Kovavisaruch, "A review of RFID localization: Applications and techniques". in *Proc. of 5th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology*, *ECTI-CON 2008.*, vol.2, pp.769-772, 2008.Article (CrossRef Link)

[5] Kim, M.,N.Y. Chong, "Direction sensing RFID reader for mobile robot navigation". *Automation Science and Engineering, IEEE Transactions on*, Vol.6, No.1, pp.44-54, 2009.Article (CrossRef Link)

[6] Chóliz, Juan, et al, "Comparison of Algorithms for UWB Indoor Location and Tracking Systems," *Vehicular Technology Conference (VTC Spring), 2011 IEEE 73rd. IEEE*, pp.1-5, 2011.Article (CrossRef Link)

[7] Atzori, Luigi, Antonio Iera, and Giacomo Morabito, "The internet of things: A survey," *Computer Networks* 54.15 (2010): 2787-2805.Article (CrossRef Link)

[8] Tesoriero, R., R. Tebar, J.A. Gallud,et al.,"Improving location awareness in indoor spaces using RFID technology". *Expert Systems with Applications*, Vol.37, No.1, pp. 894-898, 2010.Article (CrossRef Link)

[9] Yang, T. C., Liang Jin, and Juan Cheng, "An improvement CHAN algorithm based on TOA position," *Acta Electr Sin* 37 (2009): 819-822. Article (CrossRef Link)

[10] Ai, Zhongjin, and Ye Liu, "Research on the TDOA measurement of active RFID real time location system," in *Proc. of 3rd IEEE International Conference on Computer Science and Information Technology (ICCSIT), 2010. IEEE*, Vol. 2, pp.410-412, 2010.Article (CrossRef Link)

[11] Rencheng, Jin, et al, "Research on RSSI-Based Localization in Wireless Sensor Networks," in Proc. of *4th International Conference on Wireless Communications, Networking and Mobile Computing, 2008. WiCOM'08. IEEE*, pp.1-4, 2008.Article (CrossRef Link)

[12] Jinpeng, Tian, et al, "A RSSI-Based Location System in Coal Mine," in *Proc. of Microwave Conference, 2008 China-Japan Joint. IEEE*, pp.167-171, 2008.Article (CrossRef Link)

[13] Barsocchi, Paolo, et al, "A novel approach to indoor RSSI localization by automatic calibration of the wireless propagation model," *Vehicular Technology Conference, 2009. VTC Spring 2009. IEEE 69th. IEEE*, pp.1-5,2009.Article (CrossRef Link)

[14] Friedman, Jonathan, et al, “Angle-of-arrival assisted radio interferometry (ARI) target localization,” in *Proc. of Military Communications Conference, MILCOM 2008. IEEE*, pp.1-7, 2008.Article (CrossRef Link)

[15] Povalac, A.,J. Sebesta. Povalac, Ales, and Jiri Sebesta, “Phase difference of arrival distance estimation for RFID tags in frequency domain,” in *Proc. of RFID-Technologies and Applications (RFID-TA), 2011 IEEE International Conference on. IEEE*, pp.188-193,2011.Article (CrossRef Link)

[16] Zhang, R.B., J.G. Guo, F.H. Chu,et al., “Environmental-adaptive indoor radio path loss model for wireless sensor networks localization". *AEU-International Journal of Electronics and Communications*,Vol.65, No.12, pp.1023-1031, 2011.Article (CrossRef Link)

[17] Yihua, Huang, Lui Zongyuan, and Ling Guojun, “An improved Bayesian-based RFID indoor location algorithm,” in *Proc. of Computer Science and Software Engineering, 2008 International Conference on*. Vol. 3, pp.511-514, IEEE, 2008Article (CrossRef Link)

[18] Xiao, X., X. Jing, S. You,et al, “An environmental-adaptive RSSI based indoor positioning approach using RFID," *IET*, pp.127-130, 2010.Article (CrossRef Link)

[19] Tang, Lei, et al, “An adaptive location algorithm for flexible indoor environment,” *Cross Strait Quad-Regional Radio Science and Wireless Technology Conference (CSQRWC)*, 2011. Vol. 2. IEEE, 2011. Article (CrossRef Link)

[20] Han, K.,S.H. Cho, “Advanced LANDMARC with adaptive k-nearest algorithm for RFID location system,” in *Proc. of Network Infrastructure and Digital Content, 2010 2nd IEEE International Conference*, pp. 595-598, 2010.Article (CrossRef Link)

[21] Wang Yuanzhe,Mao Luhong,Liu Hui,et al.,"Research and application of RFID locatin algorithm based on reference tags,” *Journal on Communications*, Vol.31, No.2, pp. 86-92, 2010. Article (CrossRef Link)

[22] Xie, Y., J. Kuang, Z. Wang,et al, “Indoor location technology and its applications base on improved LANDMARC algorithm,” in *Proc. of Control and Decision Conference (CCDC)*, 2011 Chinese, pp2453-2458, 2011.Article (CrossRef Link)

[23] Han, K.,S.H. Cho, “Advanced LANDMARC with adaptive k-nearest algorithm for RFID location system,” in *Proc. of IC-NIDC*, pp. 595-598,2011.Article (CrossRef Link)

[24] Jing, C., L. Gengmin, Z. Xuejun,et al, “An efficient algorithm for indoor location based on RFID,” in *Proc. of Wireless Communications and Signal Processing (WCSP)*, 2011 International Conference, pp.1-4, 2011.Article (CrossRef Link)

[25] HUANG, Y., S. LV, Y. HE,et al., “An Isosceles Triangular Placement of Reference Tags for RFID Indoor Location System,” *Chinese Journal of Electronics*, Vol.20, No.3, pp.504-510, 2011. Article(CrossRefLink)

[26] Paul, A.S.,E.A. Wan, “Rssi-based indoor localization and tracking using sigma-point kalman smoothers,” *Selected Topics in Signal Processing, IEEE Journal of* Vol.3, No.5, pp.860-873, 2009.
Article (CrossRef Link)

[27] G. Jin, X. Lu, M. Park, “An indoor localization mechanism using active RFID tag," in *Proc. of the IEEE International Conference on Sensor Networks,Ubiquitous, and Trustworthy Computing, Institute of Electrical and ElectronicsEngineers Computer Society, 2006 II Taichung, Taiwan*, pp. 40–43, 2006.Article (CrossRef Link)

[28] X. Wang, X. Jiang, Y. Liu, “An enhanced approach of indoor location sensing usingactive RFID", in *Proc. of the 2009 WASE International Conference onInformation Engineering (ICIE), IEEE, Piscataway, NJ, USA*, pp. 169–172, 2009. Article (CrossRef Link)

Junhuai Li received the B.S. degree in electrical automation from Shaanxi Institute of Mechanical Engineering of China, Xi'an in 1992, M.S. degree in computer application technology from Xi'an University of Technology of China, Xi'an in 1999, and Ph.D. degree in comupter software and theory from Northwest University of China, Xi'an in 2002. He was in University of Tsukuba of Japan between March to September 2004 as a visiting scholar. He is currently a professor with School of Computer Science and Engineering, Xi'an University of Technology, China. His research interests include Inernet of Things technology, network computing.

Guomou Zhang is now a master student in School of Computer Science and Engineering, Xi'an University of Technology, China, from where he received his B.S. degree in computer science and technology from Xi'an University of Technology of China, Xi'an in 2011. His research interests include indoor position.

Lei Yu received her MS degree in Computer Science from Xi'an University of Technology (XAUT), Xi'an ,China, in 2003; She is currently a lecturer in faculty of computer science and engineer of XAUT. Her research interests are in RFID and data mining.

Zhixiao Wang received the B.S. degree from Shijiazhuang Economic University of China in 2000 and the M.S. degree from Xi'an University of Technology of China in 2004, all in computer science. He is a PhD candidate in the Department of Computer Science at Xi'an Jiaotong University, China. His current research interests include wireless and mobile networks.

Jing Zhang received the B.S. degree in automatic control from Shaanxi Institute of Mechanical Engineering of China, Xi'an in 1981, M.S. degree in software and theory from Xi'an Jiaotong University, Xi'an in 1989, and Ph.D. degree in system engineering from Xi'an Jiaotong University, Xi'an in 1994. He has worked in Department of Computer of Xi'an University of Technology since 1977, and now is a professor and the PhD supervisor of School of Computer Science and Engineering, Xi'an University of Technology, in which, he worked in Computer Training Center of Ministry of Education, P.R. China in 1982 for a short time. His curren research interests include distributed system, virtualization, grid computing and cloud computing.