A Precise RFID Indoor Localization System with Sensor Network Assistance

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Abstract: Indoor localization is very critical for medical care applications, e.g., the patient localization or tracking inside the building of the hospital. Traditional Radio Frequency Identification (RFID) technologies are very popular in this area since their cost is very low. In such technologies, each tag acts as the transmitter and the *Radio Signal Strength Indicator* (RSSI) information is measured from the readers. However, RSSI information suffers severely from the multi-path phenomenon. As a result, if in a very large area, the localization accuracy will be affected seriously. In order to solve this problem, we introduce Wireless Sensor Networks (WSNs) with only a few nodes, each of which acts as both transmitter and receiver. In such networks, the change of signal strength (referred as dynamic of RSSI) is leveraged to select a cluster of reference tags as candidates. Then the final target location is estimated by using the RSSI relationships between the target tag and candidate reference tags. Thus, the localization accuracy and scalability are able to be improved. We proposed two algorithms, SA-LANDMARC, and COCKTAIL. Experiments show that the localization accuracy of the two algorithms can reach 0.7m and 0.45m, respectively. Compared to most traditional Radio Frequency (RF)-based approaches, the localization accuracy is improved at least 50%.

Keywords: radio frequency; RFID; wireless sensor networks; hybrid; support vector regression

I. INTRODUCTION

Indoor localization is very critical in many applications, especially for medical care applications [16]. For example, inside the building of the hospital, patient tracking [1] is high demanded to figure out patient accident in time. Among various technologies, Radio Frequency Identification (RFID) technologies [3] are very popular due to their low cost. In such technologies, a number of reference tags are deployed in advance. Each tag will act as the transmitter and the *Radio Signal Strength Indicator* (RSSI) information is measured from the readers around. The position of the target tag then is estimated by the positions of those reference tags whose RSSI information are closest to target tag's RSSI information.

However, such technologies have the following drawback. Since RSSI is easily affected by the environment factors, e.g., the radio signal reflection, refraction and scattering by the object inside the room, the signal will arrive the receiver along more than one path [2]. It is referred as multi-path phenomenon. Therefore, if in a very large area, the localization accuracy will drop dramatically, even two distant target tags may have similar RSSI.

In order to overcome this drawback, in our methodology, we introduce Wireless Sensor networks (WSNs) [7][8] with only a few nodes sparsely deployed in the same area. In such networks, each node will act as both transmitter and receiver. We first utilize the change of the signal strength (also referred as dynamic of RSSI) to figure out the possible target area. Then the reference tags in this area are selected as candidate tags to calculate the final position of the target. Such methodology is more robust to the environment changes and suitable to be applied in a large area.

Under the hybrid infrastructure of densely deployed RFID and sparsely deployed WSNs, our approach contains two algorithms: SA-LANDMARC and COCKTAIL. The target is only required to carry an RFID tag. First the RSSI dynamics among WSNs are leveraged to find out the possible area for the target. Then we use the RSSI information of RFID reference tags inside this area to further locate the target. The first SA-LANDMARC algorithm uses RSSI vector Euclidean distance algorithm to find four nearest reference tags inside the possible target area to locate the target object. The second COCKTAIL algorithm makes use of Support Vector Regression (SVR) [9] to locate the target based on the information of all the reference tags inside the possible target area. The SA-LANDMARC allows efficient and accurate localization indoors, while the COCKTAIL can get higher accuracy when some easy and fast training is performed in advance. Moreover, since the RFID reader can get information of all the tags immediately, the time to rebuild the SVR model is very short.

In our experiments, we utilize TelosB [10] sensor nodes and RFID [11] in our system. Experimental results show that, when the tag distance and sensor distance are chosen as 1m and 3m, the localization accuracy of SA-LANDMRAC and COCKTAIL can reach to about 0.7*m* and 0.45*m* respectively. It shows 40% better than most of the pure RF-based approaches. Moreover, we also perform experiments for multiple targets. The localization accuracy is around 1*m*, if the density of the targets is not very high.

The rest of this paper is organized as follows. In the next section, we briefly review some related work. Section III introduces the detail methodologies of SA-LANDMARC and COCKTAIL. In the following, the experimental results and evaluation of the performance are introduced in Section IV, Finally, we conclude this paper and list our future work.

In this paper, the authors propose a novel hybrid mechanism for indoor precise localization. The approach leverages both RFID and WSNs technologies.

II. Related Work

Nowadays, there are many RF-based localization approaches. The RFID-based localization (e.g., LANDMARC [3] and VIRE [12]) is one type of the most popular RF-based localization technologies using active RFID tags. They adopt the coordinates of the *K* nearest reference tags to compute the coordinate value of the tracking tag. However, since the RSSI is easily influenced by environment, the chosen *K* nearest reference tags usually are not close to the target object. Hence if it is applied in a large field, the accuracy drops dramatically.

802.11 [6] [14] utilizes signal strength information gathered from multiple access points to locate the target objects. In order to get higher accuracy, a radio map of signal strength has to be built. Once the environment changes, it has to rebuild the radio map.

Wireless sensor networks [4][5] usually use RSSI to measure the distance among sensors, but multi-path phenomenon and other environmental factors make the real data deviate from the propagation model, sometimes it is totally different.

Transceiver-free object tracking [7][8] aims to track object which carries no device. They deploy a number of wireless nodes, and then they locate the target object by utilizing the dynamics of RSSI [7] of sensor links caused by the target. Although the dynamic of RSSI are robust to the environmental change, the densely deployed sensors cause heavy communication overhead and may introduce more interference. Hence, its localization accuracy is limited.

A recent work can very accurately localize target carrying an RFID tag [15], but it requires additional hardware to get the physical layer CSI information.

III. Methodology

As explained before, using only the RSSI or the dynamic of RSSI is not enough to accurately localize the object. So the basic idea of our approach combines the two kinds of information together for localization with higher accuracy. In our scheme, we use a sparsely deployed sensor network to get the dynamic of RSSI. Thus, the communication overhead is low and less interference is introduced. Since the dynamic of RSSI is robust to the multi-path phenomenon, in a complex indoor environment, we may accurately figure out a subarea where the object exists. After that, we utilize a densely deployed active RFID reference tags to get comprehensive information of RSSI. Then such information inside the subarea is used to further localize the object.

Before introducing the detailed algorithms, we explain some terms and depict the test infrastructure first.

-- *Static RSSI*: represents the average value of received signal strength in a very short time (e.g., 2s in our system). It utilizes the traditional RSSI value.

-- *Dynamic of RSSI*: represents the variance of received signal strength in a very short time (e.g., 2s in our system).

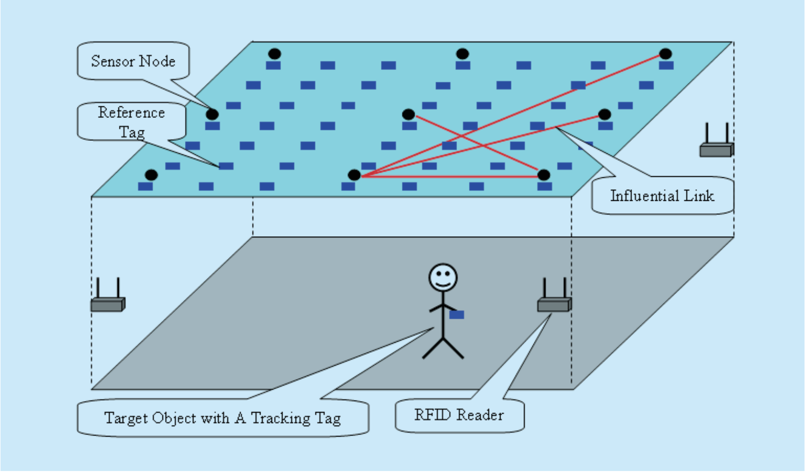

Fig.1 *The system setup of the SA-LANDMARC system*

-- *Influential link*: is the sensor link whose dynamic of RSSI is larger than an empirical threshold [8].

Our test infrastructure is depicted in Fig. 1. The setting includes a sparse sensor grid and a dense active RFID tag grid. They are put on the ceiling of our lab. The target object carries one active RFID tag. All the tags' information are read by the surrounded readers. Each sensor node acts as both transmitter and receiver. If the target object appears, the influential links tend to be clustered around the target object [8].

We have two localization algorithms to be introduced below. One is SA-LANDMARC approach, which allows efficient and accurate estimation of object locations in indoor environments. The COCKTAIL can get higher accuracy only if some easy training is performed in advance.

3.1 SA-LANDMARC

The SA-LANDMARC algorithm runs in two phases. The first phase is SA phase, which stands for "Sensor Assisted". This phase uses sensor information to figure out a subarea where the target object exists, which is referred as subarea selection phase. As a result, it is able to eliminate those reference RFID tags which are actually far away from the target object. The second phase is the localization phase. In this phase, the information of RFID reference tags inside the subarea is used to localize the object.

In the first phase, we propose two algorithms to handle subarea selection: maximal dynamic algorithm and intersection algorithm. In the second phase, we utilize the RSSI vector Euclidean distance algorithm. These three algorithms are described respectively in the following sections.

3.1.1 Maximal dynamic algorithm

Theoretically, the sensor nodes which have the largest dynamic of RSSI usually will be close to the target [8]. Therefore, the basic idea of maximal dynamics algorithm is to determine the subarea of interest by comparing the summation of the dynamics of RSSI for each subarea. Each candidate subarea in our system is defined as a square grid, covered by four adjacent sensors. As shown in Fig. 2, there are 4 subareas.

Each subarea contains 6 wireless links. For each subarea, we sum up the RSSI dynamic values of the six links. The subarea with the maximal summation value is regarded as the subarea of interest, which is the possible object area.

Suppose we have n sub-areas $\{S_1, S_2, \ldots, S_n\}$, where S_i denotes the summation of dynamics of RSSI for subarea i.

It can be computed using the following formula,

$$S_i = \sum_{j=1}^{6} d_i^j$$

where the parameter d_i^j denotes the dynamics of RSSI value of link j in subarea i.

Then we consider the subarea with the maximal summation value as the subarea of interest.

3.1.2 Intersection algorithm

Instead of utilizing the summation dynamic of RSSI for each subarea, we utilize the intersection points of those links to determine which subarea may contain the target object.

We first explain it with an example, as shown in Fig. 3. The sensor grid with 9 nodes divides the whole field into 4 subareas: *abde*, *bcef*, *degh* and *efhi*. Suppose there are 6 wireless links, whose dynamics of RSSI are larger than the threshold [8]. Totally there are 6 intersection points in the whole field, e.g., influential link *ei* and *fh* have an intersection point *p*3. Each intersection point (e.g., *p*3) has a weight value, which sums the dynamics of RSSI of the two intersection links (e.g., *ei* and *fh*). Each subarea also has its own weight. It sums the weight of all the intersection points inside and on the border area (e.g., intersection point *p*6 belongs to both cell *bcef* and *efhi*). We choose the subarea with the largest weight as candidate subarea where the target object may exist.

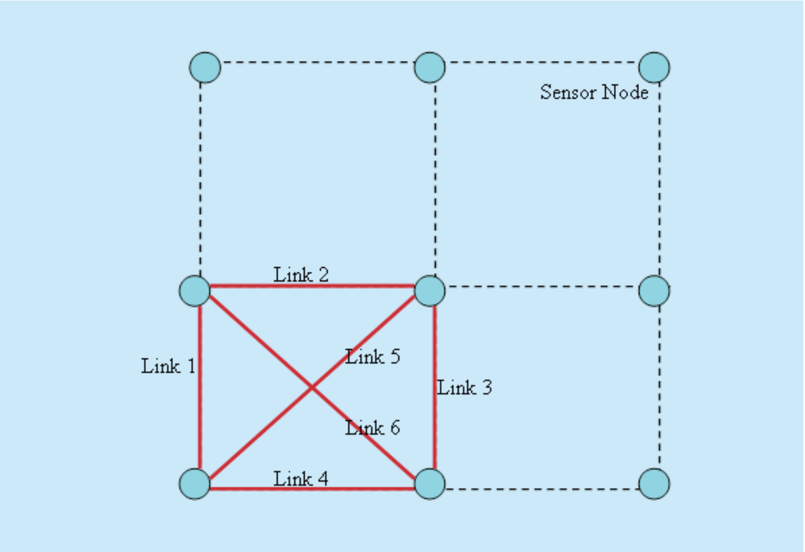

Fig.2 *The Maximal dynamic algorithm in SA phase of SA-LANDMARC and COCKTAIL algorithm*

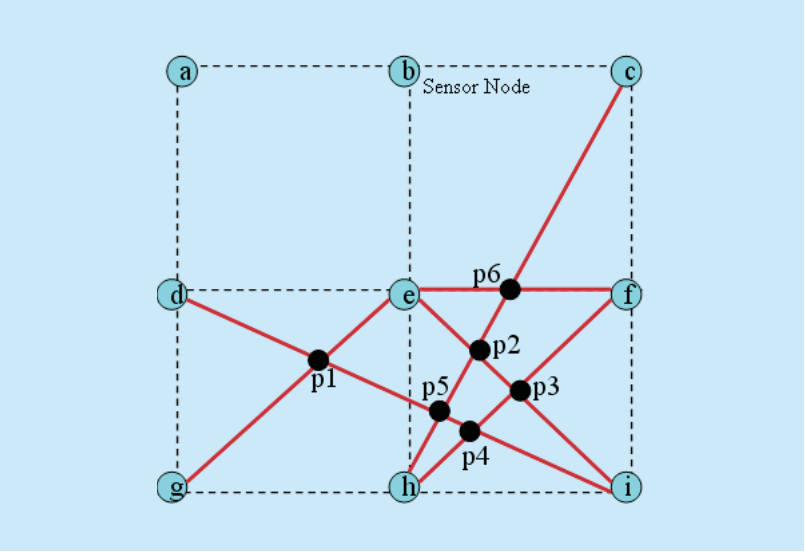

Fig.3 *The Intersection algorithm in SA phase of SA-LANDMARC and COCKTAIL algorithm*

As a general procedure, suppose our sensor grid has n subareas, each subarea i has its own weight W_i. For all the subareas, their subarea weights are denoted by a set $\{W_1, W_2, \ldots, W_n\}$. W_i can be computed using the following formula

$$W_i = \sum_{j=1}^{m} (w1_i^j + w2_i^j)$$

where parameter $w1_i^j$ and $w2_i^j$ denote the dynamics of RSSI of the two intersection links for intersection point j at subarea i. m is the total number of intersection points in or on the border of subarea i. We consider the cell having the maximum cell weight as the candidate subarea where the target object exists in.

$$W_{\max} = Max(\{W_1, W_2, \cdots, W_n\})$$

3.1.3 RSSI vector Euclidean distance algorithm

After we get the candidate subarea, in the second phase, based on the candidate RFID reference tags inside the subarea, K reference tags with high correlations to the tag carried by the target are captured. Here, the static RSSI information from tags is used, and we applied RSSI Euclidean distance algorithm [3] to find the four nearest reference tags to the target tag. Suppose we have s RFID readers and t reference tags in our system. For each reference tag i, its RSSI vector is defined as follows.

$$\vec{\theta}_i = (\theta_{i1}, \theta_{i2}, \cdots, \theta_{is})$$

Similarly, we define the RSSI vector of a tracking tag as the following equation.

$$\vec{S} = (S_1, S_2, \cdots, S_s)$$

The Euclidian distance E_i in RSSI between a reference tag i and a tracking tag can be computed using the following formula.

$$E_i = \sqrt{\sum_{j=1}^{s} (\theta_{ij} - S_{ij})^2}, \ j \in (1, s)$$

In our localization system, since we have 4 readers, the value of s is chosen as 4.

The RSSI Euclidian distance values of t reference tags to the target tag are organized as a set $\{E_1, E_2, \ldots, E_t\}$, and then from the set we choose the K reference tags with the smallest E values as the neighboring reference tags. The unknown tracking tag' coordinate (x, y) is calculated by

$$(x, y) = \sum_{i=1}^{K} w_i (x_i, y_i)$$

Here, (x_j, y_j) denotes the coordinates of the selected reference tag i. w_i is a weight value of the selected reference tag i, it is defined as the following formula empirically.

$$w_i = \frac{1/E_i^2}{\sum_{i=1}^{4} \frac{1}{E_i^2}}$$

If there are multiple objects, since each object will carry one tag, we know the number of objects. Here, suppose the number is l. In such scenario, we need to choose l subareas with largest summation weight value in the SA phase. For each subarea, the same procedure is performed as introduced above. If the objects are close to each other, fewer subareas will be found.

3.2 COCKTAIL

COCKTAIL is a more comprehensive localization algorithm. It also runs in two phases. The first phase is the same as the SA phase of SA-LANDMARC, which aims to figure out a subarea where the target object exists.

Then in the second phase, instead of just using 4 related reference tags' information, we utilize the information of all the reference tags inside the subarea, and use Support Vector Regression (SVR) to locate the target, as shown in Fig. 4.

Support Vector Regression (SVR) [9] is commonly used in forecasting the financial market and reconstruction of chaotic systems. It aims to find a hyper-plane which can accurately predict the training data. Considering our localization problem, we have many static RSSI data from reference tags. These samples are easily gotten from readers in a very short time. Therefore, the localization model is very easy to be trained to simulate the relationship between the static RSSI values and object

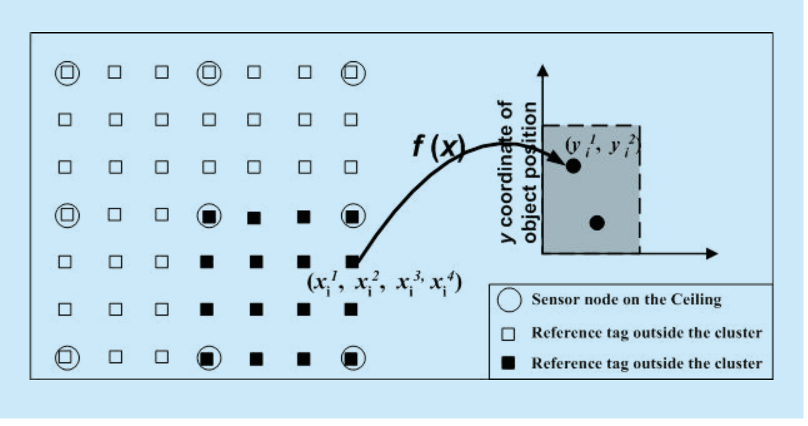

Fig.4 *COCKTAIL algorithm*

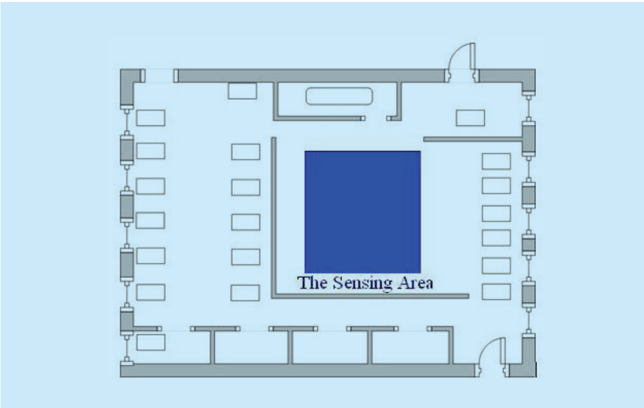

Fig.5 *Experimental environment*

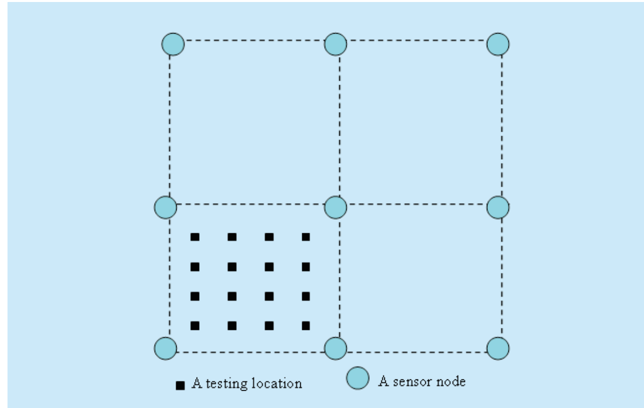

Fig.6 *Testing positions for target-clustering*

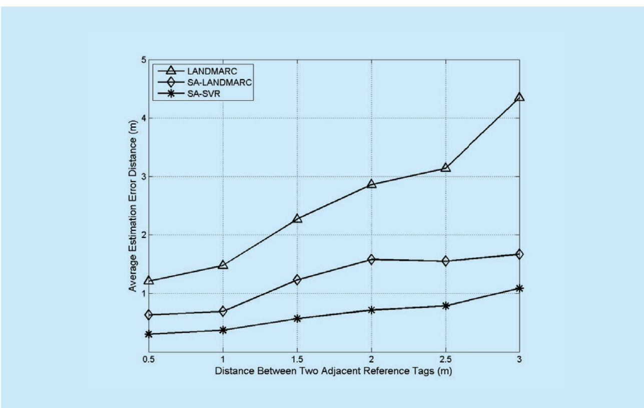

Fig.7 *The impact of tag distance*

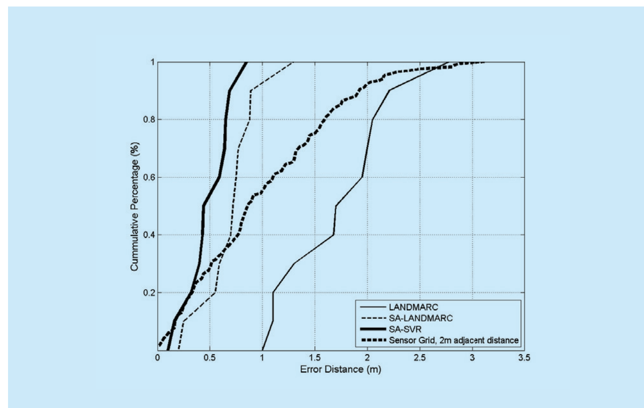

Fig.8 *Algorithm comparisons*

locations. We then can use this SVR model to perform prediction.

The space of input X is a 4 dimension data recording the static RSSI information from the 4 readers for each reference tag. In general, these data are denoted by

$$X \in R^d, X = \{x_i^d\}, x_i^d = [x_1^d, x_2^d, ..., x_n^d]$$

Here d is the number of readers. In our experiment, this value is 4. n is s number of reference tag location within the chosen subarea.

The target class Y represents the locations of reference tags. It is denoted by

$$Y \in R^k, Y = \{y_i^k\}, y_i^k = [y_1^k, y_2^k, ..., y_n^k]$$

Here k is the dimension of reference tags' location. In our setting this value is 2. n is the number of reference tags in the selected subarea. This value is decided by the size of the subarea and the density of the tags. Given the training data $\{(x_1^d, y_1^k), ..., (x_n^d, y_n^k)\}$, our goal is to find a function

$$f(x)=w\cdot\Phi(x)+b, \Phi : R^d \rightarrow f, w\in R^d, b\in \mathrm{R}$$

which has at most a tolerance parameter ε from the actually obtained targets y_i^k for all the samples and at the same time is as flat as possible [9].

The above method is included in the standard library LIBSVM [13]. We apply it to train an SVR model from X to Y under our setting. When the target carries the tag entering the field, according to the static RSSI values received by the readers, we may predict the object location by using this SVR model.

Even when environment changes, the model is easily to be retrained, since all the tag information are periodically collected by the RFID readers. Thus, we can use the model to predict the target RFID tag's locations effectively.

IV. EXPERIMENT

4.1 Experimental setup

We have performed several sets of experiments to verify the efficiency of our proposed methods. Our experiments are conducted in our lab, the layout of which is shown in Fig. 4. The sensing area is highlighted, which is a $6m \times 6m$ area. A standard deployment of our system contains $m \times m$ sensor nodes, t RFID readers and $n \times n$ reference tags, the target object also carries an RFID tag. The sensor nodes are deployed in a uniform grid on the ceiling to cover the whole sensing area. The reference tags are also deployed on the ceiling in an $n \times n$ array to cover the same sensing area. To ensure a sparse sensor deployment and a dense RFID tag deployment, m should be set smaller than n. Fig. 1 shows how the system is deployed with settings as m=3, n=7. By default, the sensor distance is 3m and the tag distance is 1m. Such sensing area can be full covered by 4 RFID readers at four corners to collect data from the reference tags. So in our system t=4.

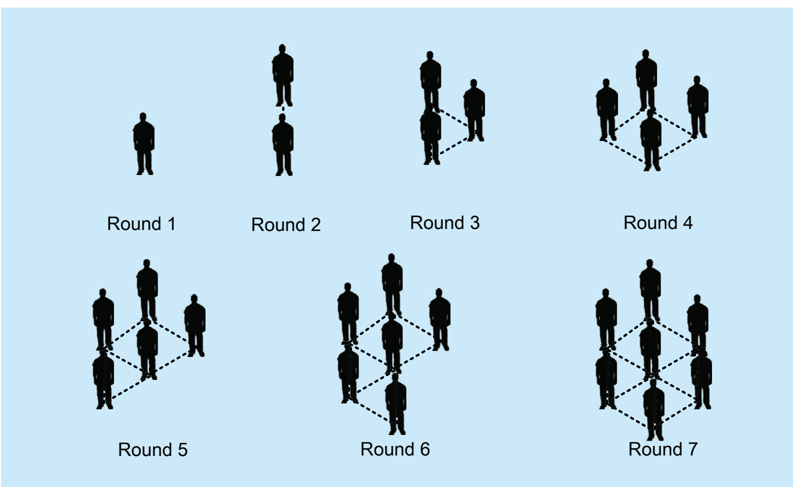

Fig.9 *Arrangement of multiple targets*

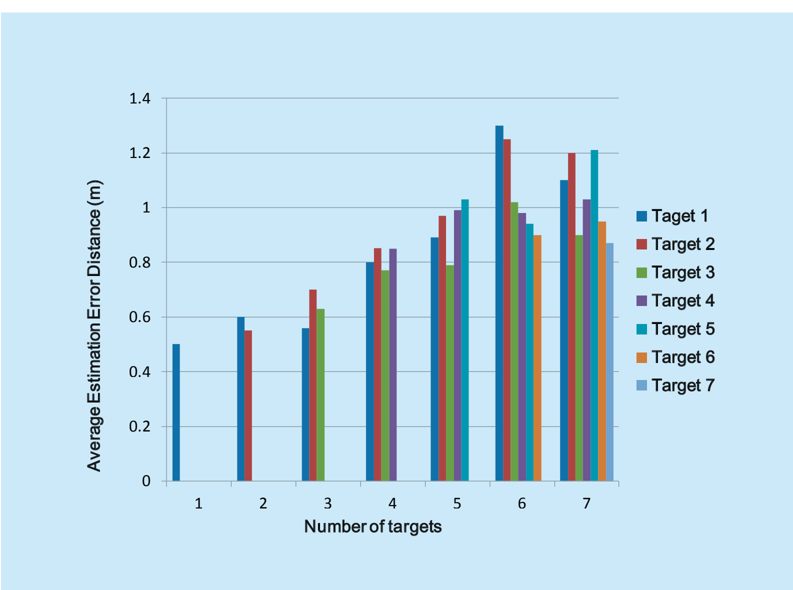

Fig.10 *Impact on accuracy of different total numbers of targets*

In our experiment, we utilize the active RFID equipments manufactured by RF Code [11] and the popular TelosB [10] sensor nodes with Chipcon CC2420 radio chips. In order to avoid the signal interference between the WSN and active RFID connections, we set the operation frequency band of the sensor nodes as 2.4GHz, which is far from our RFID hardware's operation frequency band 303.825 MHz.

Our localization runs in three phases. First in the initialization phase, each sensor builds a static table to store the static RSSI values for all its neighbors. When the target carrying a tag comes into the sensing area, it will cause the RSSI of some sensors nodes to change. Secondly, in the measurement phase, each sensor measures the dynamic of RSSI to detect the influential links. Then these data are reported via the sink node to the server computer. In the meanwhile, readers will collect all the static RSSI information from the tags, and send them to the server computer. Finally, in the last phase, based on all the received information, the system uses SA-LANDMARC or COCKTAIL algorithm to localize the target object.

4.2 Comparison of two subarea selection algorithms

In order to evaluate the two clustering algorithms, we conduct an experiment to compare their performances. We select 16 target positions in our test area to use as the testing positions (Fig. 6). Every selected position is tested 10 rounds.

The above table shows the experiment results. Obviously, the performance of intersection algorithm is much better than the performance of maximal dynamic algorithm. As shown in Table 1, almost all the testing positions are estimated correctly by the intersection algorithm. Therefore, we utilize the intersection algorithm in our later experiments.

● *Influence of tag distance*

Tag distance will influence the accuracy of static RSSI information. As a result, the localization accuracy is also influenced. In order to learn the relation between tag distance and localization accuracy, in our experiment, we perform several rounds of tests. In the initial round of test, the tag distance is set as 0.5*m*. Then for each following round of test, the tag distance increases 0.5*m* from the previous round. In the last round the tag distance is 3*m*. We also arrange a person carrying an RFID tag to represent the target and its location is randomly chosen. Then we measure the localization accuracy by comparing the real target location with the reported location from different schemes.

Based on 100 samples at each round of test, the result is depicted as Fig.7. We can see that, as the tag distance increases, no matter which algorithm we choose, short tag distance always shows better localization accuracy. Furthermore, when the tag distance grows from 0.5*m* to 1*m*, the errors of the three schemes increase quite slightly, with COCKTAIL having an average error of less than 0.5*m*. Considering the tradeoff between application requirements and deployment costs, we choose 1m as an optimal distance for reference tags for our following experiments.

4.3 Influence of sensor distance

Since introducing sensor infrastructures aims to effectively cluster the reference tags close to the target, different sensor distance will also affect the localization accuracy. Too large sensor distance has potential to count in many reference tags not close to the target. On the contrary, too small sensor distance will introduce more communication overhead among sensor and easy to produce interference.

Table I *Comparison on performance of two subarea selection algorithms*

Algorithm \ Accuracy	Number of successful selection	Number of unsuccessful selection	Accuracy
Maximal dynamic	12	4	75%
Intersection	15	1	94%

According to our empirical works [8], the sensor distance from 2*m* to 4*m* is better for localize the object without carrying any device (the tag carried by target object is unrelated to sensors). Because we have already chosen the tag difference as 1*m*, 2*m* sensor distance is too small to cover enough reference tags. Hence, we may choose the sensor distance from 3*m* to 4*m*. According to the size of our experimental area, we choose the sensor distance as 3*m* in our experiment. It means that, each sensor cell contains 16 reference tags.

4.4 Algorithm comparison

We further investigate the localization errors for different accuracy. Based on 100 random target locations in the sensing area, their comparisons are shown in Fig. 8. The advantage of sensor aided localization algorithms over the traditional reference tags based LANDMARC algorithm is obvious in Fig. 8. The average localization accuracy of our SA-LANDMARC can reach 0.7*m*, Moreover, by introducing SVR, which enables sophisticated utilization of more reference tags rather than just using information of a few selected tags, the average localization accuracy of COCKTAIL can reach about 0.45*m*. It achieves at most 75% of performance improvement comparing to LANDMARC, whose average error is 1.75*m*. Also, as we can see from the figure, the average error of a 2*m* pure sensor grid is almost 0.9*m*, which is two times larger than the COCKTAIL performance.

The experimental results demonstrate that the combination of sensor network and RFID grid in our proposed algorithms also outperform not only the pure sensor network based localization, but also the pure RFID based localization algorithms.

4.5 Localization of multiple objects

The purpose of this experiment is to investigate the impact of multiple targets on localization accuracy. We arrange several persons to serve as the targets. In the beginning round, we localize only one target. In the second round, two targets are localized with 1*m* apart. The same procedure repeats until 7 targets are tested, as shown in Fig. 9.

The experiment results are shown in Fig. 10. We can see that, the error distances become larger as the number of targets grows greater. However, we also notice that when the total number of targets is less than 4, the trend is not that obvious.

To sum up, the increased total number of targets will decrease the localization accuracy to a certain degree.

V. Conclusion and Future Work

In this paper, we propose a novel hybrid mechanism for indoor precise localization. The approach leverages both RFID and WSNs technologies. The dynamics of RSSI are obtained from the sparsely deployed wireless sensor networks, while the information of RSSI are obtained from the densely deployed RFID tags. Accordingly, two localization algorithms are proposed: SA-LANDMRAC and COCKTAIL. SA-LANDMRAC is easy to implement, while COCKTAIL has higher localization accuracy. Furthermore, COCKTAIL is adaptive to the dynamic environment, since its prediction model is easily derived from the information of reference tags and the remodeling is more efficient and rapid than other similar approaches. We also perform experiments for multiple targets.

For the future work, we are going to improve the latency of our system. The emitting time interval of our active RFID tags is fixed as 2*s*, the location sensing latency of our systems can not be less than 2s, which is a constraint to the improvement on tracking latency. Proper active RFID equipments with smaller emitting time interval are expected. If this problem can be overcome, the latency still has potential to be improved.

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