COCKTAIL: An RF-based Hybrid Approach for Indoor Localization

Dian Zhang, Yanyan Yang, Dachao Cheng, Siyuan Liu, and Lionel M. Ni
 Department of Computer Science and Engineering,
 Hong Kong University of Science and Technology
 zhangd,yanyan,tonycse,syliu,ni@cse.ust.hk

Abstract—Traditional RF-based indoor positioning approaches use only Radio Signal Strength Indicator (RSSI) to locate the target object. But RSSI suffers significantly from the multi-path phenomenon and other environmental factors. Hence, the localization accuracy drops dramatically in a large tracking field. To solve this problem, this paper introduces one more resource, the dynamic of RSSI, which is the variance of signal strength caused by the target object and is more robust to environment changes. By combining these two resources, we are able to greatly improve the accuracy and scalability of current RF-based approaches. We call such hybrid approach COCKTAIL. It employs both the technologies of active RFID and Wireless Sensor Networks (WSNs). Sensors use the dynamic of RSSI to figure out a cluster of reference tags as candidates. The final target location is estimated by using the RSSI relationships between the target tag and candidate reference tags. Experiments show that COCKTAIL can reach a remarkable high degree of localization accuracy to 0.45m, which outperforms significantly to most of the pure RF-based localization approaches.

I. INTRODUCTION

Localization is highly demanded in many important applications. In recent years, *Radio Frequency (RF)* based localization becomes one of the promising technologies. It uses *Radio Signal Strength Indicator (RSSI)* to locate the object, when both target object and some reference objects are using RF signals to communicate. Since RSSI is readily available in wireless communication without additional cost, RF-based localization has become a hot research issue in wireless networks.

In theory, the RSSI at the receiver is a function of the distance between the transmitter and the receiver as indicated in many propagation models [1]. But in practice, multi-path phenomenon and other environmental factors influence the RSSI. While the indoor layout structure and objects make the influences even more severe. Therefore, the accuracy of indoor localization is always a challenge. Especially in a large field, the accuracy often drops dramatically. For example, the popular LANDMARC [2] utilizes coordinates of K reference RFID tags whose RSSIs are nearest to the target tag to compute the location of the tracking tag.

However, the K nearest reference tags are usually not close to the target object. Sometimes they are even far away from the target if in a large deployed field. There are also some approaches, e.g., [3], which use Wireless Sensor Networks (WSNs) to localize indoor objects by employing RSSI to measure the distance among sensors. But similar problems still exist. Other approaches like [4], use radio hop count to measure the distance. But they are too inaccurate for many applications. As WiFi becomes a public source, many research works on 802.11[11] try to utilize signal strength information gathered from multiple access points to locate objects. In order to get higher accuracy, a radio map of signal strength has to be built. However, it is time consuming in the training step. Instead of using the static RSSI information as the above approaches, transceiver-free object tracking [5][6] utilizes the dynamic of RSSI [6] caused by the target to locate it. It does not require the object to carry any device. Although the method is more robust to the environment changes, the densely deployed sensors cause heavy communication overhead and may introduce more interference. As a result, its localization accuracy is limited.

In order to overcome the above drawbacks, this paper proposes an RF-based hybrid approach COCKTAIL, which combines WSNs and RFID technologies. It utilizes the resources of RSSI from RFID tags and the dynamic of RSSI from sensors. In our system, the RFID reference tags are densely deployed and the sensors are sparsely deployed. The target object carries only one active RFID tag. Our basic idea is to utilize a sparse sensor network to firstly figure out a subarea where the target exists. Then we use the information of RFID reference tags inside this subarea to further locate the target. The subarea is decided by using the dynamics of RSSI caused by the target to the wireless sensor network. Two different algorithms for object localization by applying RFID RSSI information are proposed. The first one is SA-LANDMARC. It uses RSSI vector Euclidean distance algorithm to find the four nearest reference tags inside the subarea to locate the object.

The second one is SA-SVR. It uses Support Vector Regression (SVR) [7] to locate the target based on the information of all the reference tags inside the subarea. The SA-LANDMARC allows efficient and accurate localization in indoor environments, while the SA-SVR can get higher accuracy when some easy and fast training is performed in advance. Since the reader can get information of all the tags immediately, the time to rebuild the SVR model is very short. We use TelosB [8] sensor nodes and RFID [9] in our experiments. Experimental results show that, when the tag distance and sensor distance are chosen as $1m$ and $3m$, the localization accuracy of SA-LANDMARC and SA-SVR can reach to about $0.7m$ and $0.45m$, respectively. It shows 40% better than most of the pure RF-based approaches.

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

II. RELATED WORKS

Nowadays, there are many RF-based localization approaches, e.g., active RFID technologies, 802.11 and wireless sensor networks. The RFID-based localization (e.g., LANDMARC [2]) is one type of the most popular RF-based localization technologies using active RFID tags. It adopts 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 [11] utilizes signal strength information from multiple access points to locate 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. It is very a time consuming procedure. So these approaches are limited for real time tracking applications. Wireless sensor networks, e.g., [3], 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. Some other approaches, e.g. [4], use radio hop count to measure the distance. Since the distance of each hop varies, such a method is too inaccurate for many applications. Another RF-based localization approach is transceiver-free object tracking [5] [6]. It 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 [6] of sensor links caused by the target. Although the dynamics of RSSI is robust to the environmental change, the densely deployed sensors

cause heavy communication overhead and may introduce more interference. Hence, its localization accuracy is limited.

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 COCKTAIL 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: is the average of received signal strength in a very short time (e.g., $2s$ in our system).
- Dynamic of RSSI: is the variance of received signal strength in a very short time (e.g., $2s$ in our system).
- Influential link: is the sensor link whose dynamic of RSSI is larger than an empirical threshold [6].

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 [6]. COCKTAIL has two localization algorithms. One is SA-LANDMARC approach, which allows efficient and accurate estimation of object locations in indoor environments. The other one SA-SVR can get higher accuracy only if some easy training is performed in advance.

A. 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. As a result, it is able to eliminate the reference RFID tags which are actually far away from the target object. The second phase is LANDMARC localization phase. In this phase, the information of RFID reference tags inside the subarea is used to localize the object.

In the first phase, based on the information collected from the sensors, since influential links are clustered

Fig. 1. System setup illustration

Fig. 2. SA phase

Fig. 3. SA-SVR algorithm

around the object [6], we utilize the intersection points of those links to determine the subarea which covers the target object. We begin to explain the procedure with an example. As shown in Fig. 2, the sensor grid with 9 nodes divides the whole field into 4 cells, $abde$, $bcef$, $degf$ and $efhi$. Also, there are 6 influential links with 6 intersection points in the whole field, e.g., influential link ei and fh have an intersection point $p3$. Each intersection point (e.g., $p3$) has a weight, which sums the dynamics of RSSI of the two crossing links (e.g., ei and fh). Each cell also has its own cell weight. It sums the weight of all the intersection points inside or on the border of the cell (e.g., intersection point $p6$ belongs to both cell $bcef$ and $efhi$). We choose the cell with the largest cell weight as the subarea where the object exists. As a general procedure, suppose our sensor grid has c cells, each cell i has its own cell weight W_i . So for all the cells, their cell weights are denoted by a set $W_1, W_2, \dots, W_c$. W_i can be computed as

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

Here, parameters $w1_i^j$ and $w2_i^j$ denote the dynamics of RSSI of the two crossing influential links for intersection point j at cell i . z is the total number of intersection points in or on the border of cell i . We consider the cell having the maximum cell weight as the subarea which covers the target object.

After we get the subarea where the target object exists, 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. We then apply RSSI Euclidean distance algorithm [2] to find K nearest reference tags to the target tag. Suppose we have d RFID readers and n reference tags in our system. For each reference tag i , its RSSI vector is defined as $\vec{\theta}_i = (\theta_{i1}, \theta_{i2}, \dots, \theta_{id})$. Similarly, we define the RSSI vector of a tracking tag as $\vec{S}_i = (S_1, S_2, \dots, S_d)$. The Euclidean distance E_i in RSSI between a reference tag i and a tracking tag can

be computed using the following formula,

$$E_i = \sqrt{\sum_{j=1}^d (\theta_i^j - S_i^j)^2}, j \in (1, d) \quad (2)$$

The RSSI Euclidean distance values of n reference tags to the target tag are organized as a set $\{E_1, E_2, \dots, E_n\}$. From the set we choose K reference tags with the smallest E values as the neighboring reference tags. The unknown tracking tag's coordinate (x, y) is calculated by

$$(x, y) = \sum_{i=1}^K w_i(x_i, y_i), w_i = \frac{1/E_i^2}{\sum_{i=1}^K 1/E_i^2} \quad (3)$$

Here, (x_i, y_i) denotes the coordinates of the selected reference tag i . w_i is the weight of the selected reference tag i . K is defined as 4 empirically in our experiments [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.

B. SA-SVR

SA-SVR 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 make use of Support Vector Regression (SVR) to locate the target.

Support Vector Regression (SVR) [7] 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. Consider 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 easy to be trained to simulate the relationship between the static RSSI values and object locations. We can use this SVR model to perform

prediction. The space of input X is a d dimension data recording the static RSSI information from the d readers for each reference tag. These data are denoted by

$$X \in R^d, X = \{x_i^d\}, x_i^d = [x_1^d, x_2^d, \dots, x_n^d] \quad (4)$$

Here d is the number of readers. In our experiments this value is 4. n is number of reference tag locations within the chosen subarea. The target class Y represents the locations of reference tags. It is denoted by

$$Y \in R^k, Y = \{y_i^k\}, y_i^k = [y_1^k, y_2^k, \dots, y_n^k] \quad (5)$$

Here k is the dimension of reference tags' location. In our setting this value is 2. n is 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 $\{(x_1^d, y_1^k), \dots, (x_n^d, y_n^k)\}$, our goal is to find a function

$$f(x) = w \cdot \Phi(x) + b, \Phi: R^d \rightarrow f, w \in R^d, b \in R \quad (6)$$

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 [7].

The above method is included in the standard library LIBSVM [10]. We apply it to train an SVR model from X to Y under our setting. When the target carrying the tag enters the field, according to the static RSSI values received by the readers, we may predict the object location by using the SVR model. 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. PERFORMANCE EVALUATION

A. Experiment Setup

We have performed several sets of experiments to verify the efficiency of COCKTAIL. Our experiments are conducted in our lab, with the layout shown in Fig. 4. The sensing area is highlighted, which is a $6m \times 6m$ area. Our standard deployment contains $m \times m$ sensors, d RFID readers and $n \times n$ reference tags. The target carries an RFID tag. The sensors 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 area. To ensure a sparse sensor deployment and a dense RFID tag deployment, m is set smaller than n . Fig. 1 shows our settings with $m = 3$ and $n = 7$. 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 $d = 4$.

In our experiments, we utilize the active RFID equipments manufactured by RF Code [9] and TelosB [8]

sensors with Chipcon CC2420 radio chips. To avoid the signal interference between the WSN and active RFID connections, we set the sensor operation frequency band as 2.4GHz, which is far from our RFID hardware's operation frequency band 303.825 MHz. Our localization runs in 3 phases. In the initialization phase, each sensor builds a 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 sensor nodes to change. In the second phase, each sensor measures the dynamic of RSSI to detect the influential links. The data are reported via the sink to the server. In the meanwhile, readers will collect all the static RSSI information from the tags, and send them to the server. In the last phase, based on all the received information, COCKTAIL is used to localize the target object.

B. Influences of tag distance

Tag distance will influence the localization accuracy. In order to learn their relationship, we perform several rounds of tests. In the initial round, the tag distance is $0.5m$. For each following round, the tag distance increases $0.5m$ from the previous round. In the last round the tag distance is $3m$. We also arrange a person carrying an RFID tag to represent the target. Its location is randomly chosen. 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, the result is depicted in Fig. 5. 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 $0.5m$ to $1m$, the errors of the three schemes increase quite slightly, with SA-SVR having an average error of less than $0.5m$. Considering the tradeoff between application requirements and deployment costs, we choose $1m$ as an optimal distance for reference tags for our following experiments.

C. Influences 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. According to our empirical works [6], the sensor distance from $2m$ to $4m$ 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 $1m$, $2m$ sensor distance is too small to cover enough reference tags. Hence, we may choose the sensor distance from $3m$

Fig. 4. Experimental environment

Fig. 5. The impact of tag distance

Fig. 6. Algorithm comparisons

to 4m. According to the size of our experimental area, we choose the sensor distance as 3m in our experiment. It means that, each sensor cell contains 16 reference tags.

D. Algorithm comparisons

We investigate the localization errors for different schemes. Based on 100 random target locations in the sensing area, their comparisons are shown in Fig. 6. The advantages of sensor aided localization over LANDMARC is obvious in Fig. 6. The average localization accuracy of SA-LANDMARC can reach 0.7m. 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 SA-SVR can reach 0.45m. It achieves at most 75% of performance improvements comparing to LANDMARC. Also, the average error of a 2m pure sensor grid is almost 0.9m, which is two times larger than the SA-SVR performance. The experimental results demonstrate that COCKTAIL outperform not only the pure sensor network based localization, but also the pure RFID based localization.

E. Latency

Since the emitting time interval of our active RFID tags is fixed as 2s, the localization latency of our systems can not be less than 2s. if proper active RFID equipments with smaller emitting time interval are obtained, the latency still has potential to be improved.

V. CONCLUSION AND FUTURE WORK

In this paper, we presented a novel hybrid mechanism COCKTAIL for indoor precise localization. It utilizes two kinds of information, static RSSI and the dynamics of RSSI. The dynamics of RSSI are obtained from the sparsely deployed sensors, while the information of static RSSI are obtained from the densely deployed RFID tags. COCKTAIL has two localization algorithms: SA-LANDMARC and SA-SVR. SA-LANDMARC is easy to implement, while SA-SVR has higher localization accuracy. Moreover, SA-SVR is very adaptive to the dynamic environment, because its prediction model is

easily derived and the remodeling is more efficient and rapid than other similar approaches. For the future work, more experimental work is preferred for multi-target localization. By analyzing the characteristics of real indoor multi-object scenarios, we attempt to propose some solutions to that in the future.

ACKNOWLEDGE

This research was supported in part by Hong Kong RGC Grant HKUST617908, China NSFC Grant 60933011, the National Basic Research Program of China (973 Program) under Grant No. 2006CB303000, the National Hi-Tech R&D Program of China (863 Program) under Grant No. 2008AA01A324, the National Science and Technology Major Project of China under Grant No. 2009ZX03006 – 001, and the Science and Technology Planning Project of Guangdong Province, China under Grant No. 2009A080207002.

REFERENCES

- [1] T. S. Rappaport, "Wireless communications: principles and practice", in 2nd ed., Upper Saddle River, NJ: Prentice Hall PTR, 2002.
- [2] L. M. Ni, Y. Liu, Y. C. Lau, and A. P. Patil, "LANDMARC: indoor location sensing using active RFID", in *Proceedings of PerCom*, 2003.
- [3] C. Whitehouse, "The design of calamari: an ad-hoc localization system for sensor networks", in *Master's thesis, University of California at Berkeley*, 2002.
- [4] R. Nagpal, H. Shrobe, and J. Bachrach, "Organizing a global coordinate system from local information on an ad hoc sensor network", in *Proceedings of IPSN*, 2003.
- [5] M. Youssef, M. Mah and A. Agrawala, "Challenges: device-free passive localization for wireless environments", in *Proceedings of MobiCom*, 2007.
- [6] D. Zhang, J. Ma, Q. Chen, and L. M. Ni, "An RF-based system for tracking transceiver-free objects", in *Proceeding of PerCom*, 2007.
- [7] A. J. Smola and B. Scholkopf, "A tutorial on support vector regression", in *Statistics and Computing* 14(3):199-222, 2004.
- [8] XBOW Corporation, "TelosB mote specifications" <http://www.xbow.com/Products/productdetails.aspx?sid=252>.
- [9] R. Want, "An Introduction to RFID Technology", in *Proceedings of IEEE Pervasive Computing*, vol. 06, 2006.
- [10] [Online]. Available: <http://www.csie.ntu.edu.tw/~cjlin/libsvm/>
- [11] J. Pan, J. T. Kwok, Q. Yang, J. J. Pan, "Adaptive Localization in a Dynamic WiFi Environment Through Multi-view Learning", in *Proceeding of AAAI*, 2007.