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Dual-modal Indoor Mobile Localization System based on Prediction Algorithm

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Abstract—**Object localization defines an important application for wireless sensor networks. In this paper, we present a hybrid of dual-modal mobile localization system to support the object tracking in indoor environment. In order to decrease the system cost and simplify the sensor deployment, we implement the localization by the received radio signal strength approach and the unscented Kalman filter (SPKF) algorithm in active and passive dual-modal architecture. We realize the system by employing the wireless sensor network and the LAN medium Zigbee/802.15.4. Experimental results demonstrate that the hybrid mobile localization system can significantly improve the localization accuracy and robustness, and reduce the cost of communication among sensor nodes while mobile user is moving in the indoor environments.**

Keywords-mobile localization system; dual-modal; Unscented Kalman Filter;

I. INTRODUCTION

The localization, locating a mobile object, is a fundamental problem in mobile motion supervision and control. Typically, the outdoor localization uses Global Positioning System (GPS) [1], which is widely applied for navigation of the vehicles, ships, and airplanes. However, the GPS signal is not available for locating the object inside the building. Recently, many applications demand the location messages in indoor environments, e.g., locating patients in a hospital [2,3,4], tracking a robot in a room, and guiding a visitor in a public building. The importance and promise of location-aware applications has led to the design and implementation of such systems for indoor localization.

Several indoor location and tracking systems have been developed. The Active Badge [5] is developed at Olivetti Research Laboratory (now AT&T Cambridge). In this system, objects are tracked by attaching a badge, which periodically transmits its unique ID using an infrared transmitter. Fixed infrared receivers pick up this information and the object location is computed. But its line-of–sight requirement and short-range signal transmission are two major limitations that suggest it to be less effective in practice for indoor location with a room-sized precision per about 15 seconds. Cricket system uses the time difference of arrival (TDOA) between radio frequency (RF) and ultrasound to estimate distance and adopts the triangulation method to calculate location [6,7]. It can accurately locate 4×4 square-feet regions with an average error nearly 10cm, yet the cost is so exorbitant that it is inaccessible to most applications. Additionally, it is proved easily affected and sensitive to the direction for adopting ultrasound to localization in experiments. RADAR [8], developed by Microsoft Research group, is an RF based system for locating and tracking object inside building. It uses RF signal strength information gathered at multiple receiver locations to triangulate the target's coordinates. Triangulation is done using both empirically determined and theoretically-computed signal strength information. The major merit is that it is easy to setup, the drawback is that it cannot guarantee the location precision and Omni-direction. It determinates objects' location within about 3-4.3 meters of their actual location with 50 percent probability. LANDMARC [9] presents a location-sensing prototype system based on active Radio Frequency Identification (RFID) that carried by objects to provide their location. It improves the overall localization accuracy by utilizing the concept of reference tags. Nevertheless, its lethal drawback is that it needs to take 30 seconds to locate an object, which is unendurable in an environment with lots of mobiles. The Cicada system [10] is based on TDOA algorithm to measure distances, and uses the slide window filter and least square fitting for the rough distance correction. It can provide the coordinates within 5cm average deviation, but its applications are also limited by the ultrasound signal and its energy cost is unacceptable. So in order to supply a good performance, the indoor localization system should satisfy the requirements of precision, robustness and cost effective.

Being different from those architectures above, we try to build a RF localization system for tracking short distance objects. The main objective is to improve the localization precision and reduce the energy cost. In this paper, we present the location estimation problem of a moving device in indoor location environment and a hybrid mobile localization system, which combines active and passive architecture. It is an adaptive system that can select the different architecture for various motions of the mobile device. This dual-modal system is nearly as accurate as the active mobile architecture system while reduces a great deal of communications between anchor nodes. The experiments show that this system has good performance, especially in the following aspects: higher precision, higher robustness, and lower energy cost.

The rest of this paper is organized as follows: in section 2, we describe the system structure and the hardware. In section 3, we discuss the radio frequency signal model,

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localization algorithm and the architecture of the dual-modal localization system. In section 4, we present several experiments and evaluation criterion, followed by conclusions in section 5.

II. THE SYSTEM STRUCTURE FOR DUAL-MODAL LOCALIZATION

In the proposed localization system, we choose Micaz mote of Crossbow Technology INC. as our sensor node, which is shown as Fig.1. Each node is a small hardware platform consisting: an RF transceiver CC2420 for sending or receiving RF signal which is used for both object localization and data transmission, a microcontroller ATMega128L that runs various algorithms, and other associated hardware such as Logger flash and 51-pin Expansion Connector for interfacing with a host device. The software running on the nodes provides both RF transmission and an Application Program Interface (API) to set different system parameters.

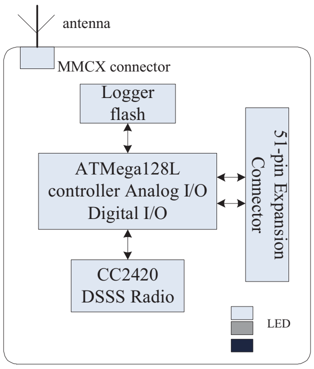


Figure 1. The structure of Micaz mote

There are two types of sensor nodes: beacons and listeners. More than four beacons are fixed on the indoor ceilings with their own definite coordinates that are measured and stored in advance, while the listener is installed on the mobile device. In addition, a particular beacon is used as the base station to collect the location information and transmit it to the computer. The coordinate of listener is unknown before being computed whether it is moving or static. In addition, there is a particular beacon unit used as the base station to collect the location information. The structure is shown in Fig.2, the mobile device is moving into the lab while 5 beacons are deployed in the ceiling, and the communication among beacons, listener and base station is wireless.

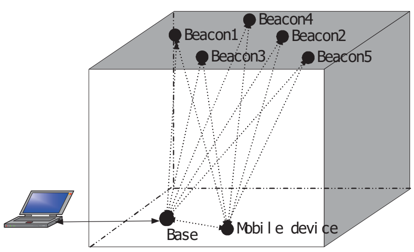


Figure 2. The framework of the hybrid system

III. THE ALGORITHMS AND SOFTWARE

A. *Structure of the hybrid system*

The underlying localization problem requires three components that are combined in different ways depending on the architecture. The first component is the signal strength predictor, wherein SPKF [11] algorithm is applied to accurately achieve next received signal strength (RSS). The second component is a modal discriminator, which realizes the transition from the active mode to the passive mode, and vice versa. It also sets the covariance threshold to select localization architecture. The third component is a position estimator, which includes dynamic triangular algorithm (DTN) [12] and least-squares method (LSM) for the localization, which is selected depending on the modal discriminator.

B. *Strength prediction and localization algorithm*

1) The radio signal model: we record the *RSS*s and distances between the sensor nodes and mobile device, and use Maximum Likelihood method to find a propagation model for the fading channel. The Measured signal strength meets the channel model that is obtained by using the following equation

$$RSS(d) = RSS(d_0) - 10n\log(d/d_0) \tag{1}$$

Where $RSS(d)$ is the mean signal strength that is received form the mobile user, $RSS(d_0)$ is the received signal strength in dB at a reference distance, and n is the path loss exponent.

The estimation of the distance is written as

$$\hat{d} = d_0 10^{\frac{RSS(d_0)-RSS(d)}{10n}} \tag{2}$$

2) SPKF prediction algorithm: For tracking mobile device, the SPKF approach utilizes the unscented Kalman filter (UKF) to predict received signal strength. The UKF is an application of the scaled unscented transformation; it uses a recursive minimum mean-square-error (RMMSE) estimation to propagate the sigma points through the state equation to obtain some high order information by the first order approximation.

The SPKF addresses the problem to estimate the state and measurement function modeled as the following nonlinear auto-regression process:

$$\boldsymbol{X_k = F(X_{k-1}, w)} + \boldsymbol{A}\cdot v_{k-1} \tag{3}$$

$$\boldsymbol{Y_k = H(X_{k-1}, r) + n_k} \tag{4}$$

Where $x_k = RSS_k, (k = 1,...,\mathrm{n})$ denotes the true RSS at step k, and sequence y_k is the kth measurement. $\boldsymbol{w}$ and $\boldsymbol{r}$ are the weight vector.

The SPKF algorithm can be described as follows:

Initialization states of mean value and autocorrelation as equation (5) and (6):

$$\overline{RSS}_0 = \mathrm{E}[RSS_0] \tag{5}$$

$$P_0 = \mathrm{E}\left[\left(RSS_0 - \overline{RSS}_0\right)\left(RSS_0 - \overline{RSS}_0\right)^{\mathrm{T}}\right] \tag{6}$$

Let $\bar{X}_0^a = \mathrm{E}\left[RSS^a\right] = \left[\overline{RSS}_0^{\mathrm{T}} \quad 0 \quad 0\right]^{\mathrm{T}}$, the autocorrelation is

$$\boldsymbol{P}_0^a = \mathrm{E}\left[\left(RSS_0^a - \overline{RSS}_0^a\right)\left(RSS_0^a - \overline{RSS}_0^a\right)^{\mathrm{T}}\right] = \begin{bmatrix} P_0 & 0 & 0 \\ 0 & Q_0 & 0 \\ 0 & 0 & R_0 \end{bmatrix}$$

The Procedure is implemented as:

Updating the iterative counter, let $k = k + 1$ and generate sigma points:

$$\chi_{k-1}^a = \left[\overline{RSS}_{k-1}^a \overline{RSS}_{k-1}^a \pm \sqrt{(n_a + \lambda) P_{k-1}^a}\right] \tag{7}$$

Then calculate the time update procedure:

$$\chi_{k/k-1}^x = f\left(\chi_{k-1}^x, \chi_{k-1}^v\right) \tag{8}$$

$$\overline{RSS}_{k/k-1} = \sum_{i=0}^{2n_a} W_i^{(m)} \chi_{i,k/k-1}^x \tag{9}$$

$$\boldsymbol{P}_{k/k-1} = \sum_{i=0}^{2n_a} W_i^{(c)} \left[\chi_{i,k/k-1}^x - \overline{RSS}_{k/k-1}\right]\left[\chi_{i,k/k-1}^x - \overline{RSS}_{k/k-1}\right]^{\mathrm{T}} \tag{10}$$

Where, $\overline{RSS}_{k/k-1}$ is the estimated posteriori state, $\boldsymbol{P}_{k/k-1}$ is the covariance estimates

$$y_{k/k-1}^x = h\left(\chi_{k-1}^x, \chi_{k-1}^n\right) \tag{11}$$

$$\bar{y}_{k/k-1} = \sum_{i=0}^{2n_a} W_i^{(m)} y_{i,k/k-1}^x \tag{12}$$

From (11) and update the measurement state:

$$\boldsymbol{P}_{\bar{y}_k \bar{y}_k} = \sum_{i=0}^{2n_a} W_i^{(c)} \left[y_{i,k/k-1} - \overline{RSS}_{k/k-1}\right]\left[y_{i,k/k-1} - \overline{RSS}_{k/k-1}\right]^{\mathrm{T}} \tag{13}$$

$$\boldsymbol{P}_{x_k y_k} = \sum_{i=0}^{2n_a} W_i^{(c)} \left[\chi_{i,k/k-1} - \overline{RSS}_{k/k-1}\right]\left[y_{i,k/k-1} - \bar{y}_{k/k-1}\right]^{\mathrm{T}} \tag{14}$$

From equation and (14), we get the Kalman gain:

$$\boldsymbol{K_k} = \boldsymbol{P}_{x_k y_k} \boldsymbol{P}_{\bar{y}_k \bar{y}_k}^{-1} \tag{15}$$

Using the posteriori state estimate the $\overline{RSS}_k$ can be concluded as:

$$\overline{RSS}_k = \overline{RSS}_{k/k-1} + \boldsymbol{K_k}\left(y_k - \bar{y}_{k/k-1}\right) \tag{16}$$

Then calculate the posteriori error covariance estimate as:

$$\boldsymbol{P}_k = \boldsymbol{P}_{k/k-1} - \boldsymbol{K_k} \boldsymbol{P}_{\bar{y}_k \bar{y}_k} \boldsymbol{K}_k^{\mathrm{T}} \tag{17}$$

If $k < \mathrm{M}$, where M is the number of iteration, go on iteration. Then output the prediction result $\overline{RSS}_k$ of the moving object at $t = k$ and $RSS_{\mathrm{pred}k}^k = \overline{RSS}_k$

3) Descript the two localization algorithmss: When the mobile device is static or moving in a regular way, the least-square method is applied to optimize the position estimation of the multilateral measurement. It minimizes the mean-squared error of a set of simultaneous non-linear equations as: $\sum_{i=1}^{n}(\| \hat{p}_i - p_i \| - d_i)^2$, where $\hat{p}_i$ is the estimated position of the mobile device, $\| \hat{p}_i - p_i \|$ is the estimated distance of the beacon and listener, d_i is the true distance.

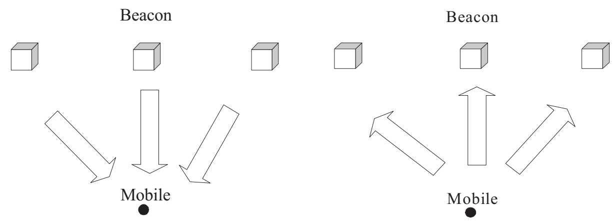
While the mobile device is moves in an irregular way, such as sudden acceleration, deceleration or circle motion, the dynamic triangular algorithm is applied to estimate the position. The DTN includes the following step:

- Beacons broadcast *RSS*s from mobile device, and the beacon that receives the strongest strength becomes the master node, while other beacons become slave nodes. Then they build the local coordinate system and set the coordinate of mobile as $(x_1 + d_1\cos\theta, y_1 + d_1\sin\theta)$.
- The location server calculates the cost functions $CF_\theta = \sqrt{Error_{1\theta}^2 + Error_{2\theta}^2}$ at each angle on the mapping circle and searches θ_{Min} to achieve the minimum cost function, and calculate the estimation location of mobile device by

$$\hat{D} = (\hat{x}, \hat{y}) = \left(x_1 + d_1 cos\theta_{\mathrm{Min}}, y_1 + d_1 sin\theta_{\mathrm{Min}}\right).$$

C. Dual-modal architecture

The active mobile architecture, as illustrated in Fig.3 (a), has an active transmitter on each mobile device, which periodically broadcasts a message on a wireless channel. Receivers are deployed to acquire the signals from listens for such broadcasts. Typically, each receiver propagates this location information to a central database that then updates the location of each mobile device. In contrast, the passive mobile architecture is illustrated in Fig.3 (b), inverts the transmitter and receiver locations. Here, beacons are deployed at known positions in the infrastructure periodically and transmit their message on a wireless channel, while the receivers on mobile devices listen to each beacon passively.



(a) Passive mode (b) Active mode

Figure 3. Passive and Active Mode Schematic Diagram

Generally, in an active mobile mode, the system has a good performance in tracking mobile device, as the listener on the mobile device can easily compute a position estimation using simultaneous distance samples received from multiple beacons. Moreover, we selected DTN algorithm as the estimator. However, in this modal, the communications among nodes increase greatly. Contrastly, in a passive mobile approach, the listener feeds the non-simultaneous distance samples to LSM estimator to compute the position estimation; the LSM estimation is subject to large errors because there is a time delay for its estimation works with distance samples, which may have been obtained when the device was in a different position. Therefore, we choose DTN algorithm, as it has good performance in this situation.

We develop the following solution for the transition between passive and active mode on the mobile device:

1) As long as the covariance of UKF is smaller than the threshold, the listener on mobile device does not transmit any information, only beacons can do so. In this situation, the estimator judges the mobile is in a regular motion, we use the passive mobile system due to its scalability and guaranteed user-privacy.

2) When the device experiences a sudden non-linear acceleration or a turn, the covariance of UKF is deemed large, and then it becomes an active transmitter. The listener then generates a concurrent RF message, with the message having no information in it other than a randomly generated nonce.

3) If a beacon receives an RF message generated by a mobile device, it waits for a short random period and broadcasts the nonce (set by the mobile) together with the RSS. During the broadcast, the beacons use a simple CSMA scheme with randomized back-off to avoid RF collisions. After receiving this information from nearby beacons, the listener can compute its position accurately since the simultaneity condition holds for these distance samples. Next, the listener uses this position estimation to reset its location modal. The flow chart of the dual-modal tracking algorithm is shown in Fig.4.

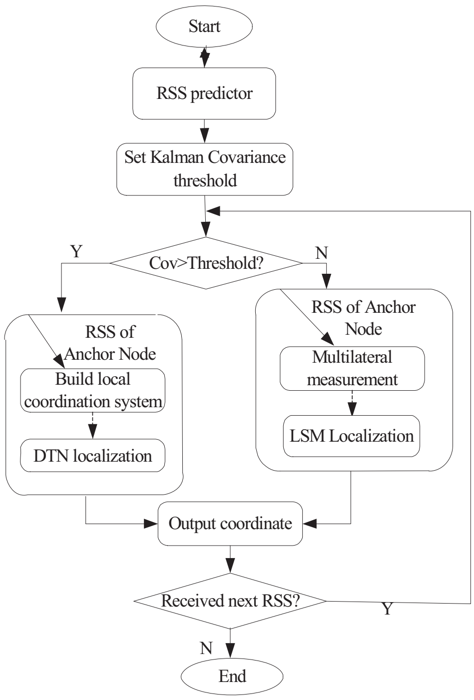


Figure 4. The Procedure of Location Estimation System

In order to avoid time synchronization among the beacons and the listeners, when the mobile and the beacons have competition for transmitting the message requesting ranging information, we have not set aside a unique time slot, but simply choose a CSMA scheme to enable a passive listener to transit to an active mode. One disadvantage of this scheme is that beacons need continuously to listen to the RF channel for possible mobile transmissions. Since the hybrid system would typically contain a mixture of both active and passive listeners at any given time, an appropriate balance between the two modes which can be achieved with some tuning.

IV. Experiments and Evaluation

We have implemented the proposed location system on Micaz sensor motes. The experiments are conducted in our experiment lab. With the implementation of different tracking schemes, users of the dual-modal system can take advantage of a variety of predictive tracking techniques for applications involving continual or unpredictable device motion.

A. Metrics and Setup

We conduct a series of experiments to evaluate performance of the proposed dual-modal position estimation system. The available radio frequency channels are scanned to avoid interference from Wireless LAN at the test area. We adopt the event-driven mode to change the coordinates of mobile device. In the experiment, the sampling period is 50millisecond, and the localization period is 200millisecond.

In the standard setup, we place several static RF beacons (n > 4) in the ceil of the 6m × 10m lab environment, while the mobile device as objects being tracked is moving into the lab as illustrated in Fig.5.

Figure 5. Deployment of the lab

1) The setup-uniform-acceleration & deceleration motion: The velocity of mobile device is initialized as 0m/s and the acceleration as $0.15\ \mathrm{m/s^2}$. After 6 seconds, it moves with the constant velocity of 0.9m/s for 4 seconds. Then the mobile device moves at deceleration of $0.3\ \mathrm{m/s^2}$ until stop. The whole process cost 13 seconds. The mobile moves in five orientation of radical motion to experience the whole monitoring region. There are 56 localization results in each motion, and we get 280 localization results totally.

2) The circular motion:

In this experiment, the mobile device moves at three circular trajectories with the radius of 0.7m, 0.9m and 1.2m separately, and at each time the mobile's velocity is $0.1\ \mathrm{rad/s}$, $0.2\ \mathrm{rad/s}$ and $0.3\ \mathrm{rad/s}$. It costs 60 seconds, 30 seconds and 20 seconds separately in each velocity. In all, there are 525 localization results.

B. Performance Analysis and Experiment Result

We now look at three important architectural properties and discuss how well the hybrid approach performs in each case.

1) Convenience for deployment:

In the proposed hybrid system, beacons are placed on the ceiling, the listeners are only need to be taken; these nodes are wireless connected, so it is easy to deploy and portable.

2) Position precision and robustness:

The key metric for evaluating a localization technique is the accuracy of the location estimates. Our main result is that the hybrid system is nearly as accurate as the active mobile system in tracking moving devices, while maintaining the advantages of the passive mobile system.

a) Mean Square Error (MSE):

The MSE is used to determine the prediction performance comparison between the SPKF algorithm, WGP algorithm and the EKF algorithm. At the Run-time stage we put the measured *RSS*s which generated from mobile to the SPKF, WGP and EKF, then get the predicted *RSS* . MSE can be obtained by the following equations:

$$\mathrm{MSE}_{\mathrm{SPKF}} = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(RSS^{i}_{\mathrm{preds}} - RSS^{i})^2}$$
$$\mathrm{MSE}_{\mathrm{WGP}} = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(RSS^{i}_{\mathrm{predw}} - RSS^{i})^2} \quad (18)$$
$$\mathrm{MSE}_{\mathrm{EKF}} = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(RSS^{i}_{\mathrm{prede}} - RSS^{i})^2}$$

Where, the $\mathrm{MSE}_{\mathrm{SPKF}}$, $\mathrm{MSE}_{\mathrm{WGP}}$ and $\mathrm{MSE}_{\mathrm{EKF}}$ is on behalf the MSE of SPKF, WGP and EKF algorithm respectively. RSS^{i}_{preds} , RSS^{i}_{predw} and RSS^{i}_{prede} is the *i*th predicted RSS of the SPKF, WGP and EKF algorithm, the RSS^{i} is the *i*th truth RSS which is received from the mobile device. Fig.6 demonstrate the experiment results, it is obvious that the SPKF algorithm gets the minimum MSE.

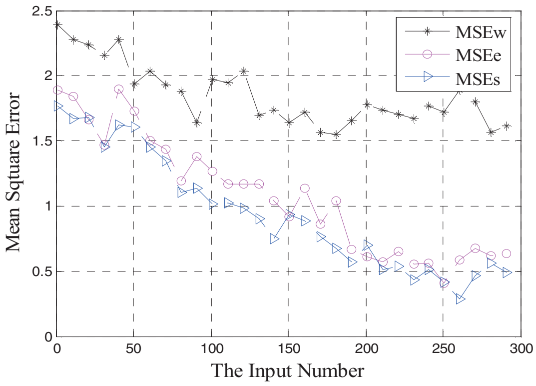


Figure 6. Comparison of mean square error

b) Mean Distance Error (MDE):

In order to evaluate the high accuracy of dual-modal localization system, we use the MDE to determine the performance of the proposed architecture, and compare the passive architecture with the active architecture. The MDE can be described by the following equation:

$$\mathrm{MDE}_{\mathrm{active}} = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(d^{i}_{\mathrm{active}} - d^{i})^2}$$
$$\mathrm{MDE}_{\mathrm{passive}} = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(d^{i}_{\mathrm{passive}} - d^{i})^2} \quad (19)$$
$$\mathrm{MDE}_{\mathrm{dual}} = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(d^{i}_{\mathrm{dual}} - d^{i})^2}$$

Where $\mathrm{MDE}_{\mathrm{active}}$, $\mathrm{MDE}_{\mathrm{passive}}$ and $\mathrm{MDE}_{\mathrm{dual}}$ is the MDE of the active, the passive and the dual-modal architecture separately; the d^{i}_{active} , d^{i}_{passive} and d^{i}_{dual} demonstrate the *i*th estimate distance under the three above architectures respectively. And d^{i} is the *i*th true distance of the mobile to beacon.

As shown in the Fig.7, the proposed dual-modal localization system performs quite well, and its MDE is between 1.5m to 2m. Although this tracking result is not as well as the active architecture, it is smaller than 0.5m after inputting 200, but it performs much better than the passive architecture and maintains high position estimation accuracy and high robustness with lower energy cost of the system.

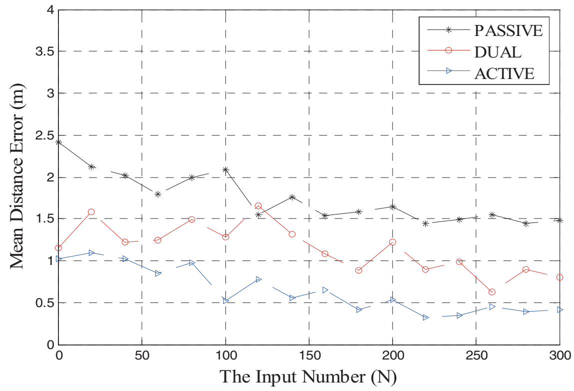


Figure 7. Comparison of mean distance

3) Computational complexity and communication cost:

In the proposed dual-modal localization system, we adopted the SPKF for prediction, the UKF captures the posterior mean and covariance accurately to between 2nd and 3rd order (Taylor series expansion) for any nonlinearity. Contrastly, in extended Kalman filter (EKF) variables propagate analytically through the first-order linearization of the nonlinear system. This can lead to sub-optimal performance and sometimes divergence of the filter. Theoretically, EKF is suitable for the nearly linear system, and our location system is non-linear, so the precision of UKF is higher than EKF in the proposed system. It displays the value of $\boldsymbol{P}_k$ versus the iteration in Fig.8, and the UKF is almost convergence by the 15th iteration. Therefore, it can achieve high accuracy with relative low computational complexity.

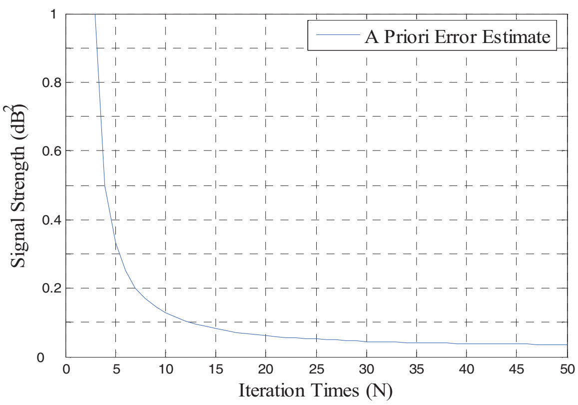


Figure 8. Convergence rates of UKF

V. CONCLUSION

We present an indoor RF localization system by using the hybrid dual-modal architecture. It has an adaptive structure that can select the different architecture for various motions of the object, and a transition method of setting the unscented Kalman filter's covariance as the threshold. Moreover, we use SPKF algorithm to reduce the reflection and scattering effect on radio signal propagation in the indoor environment. In our experiment, it compares the performances of the active mobile architecture, the passive mobile architecture and the dual-modal architecture system. The results demonstrate that the hybrid approach can significantly reduce the energy cost of the system, while preserve quite acceptable precision and robustness. In conclusion, this method is a dependable cost-effective localization system for accurate indoor location sensing.

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