Block Localization Methods for Mobile Robot Tracking and Navigation

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***Abstract*—Wireless information transmission tools have been common in buildings and houses. Using the information which wireless anchor nodes periodically broadcast, a mobile robot can estimate its own location in indoor environments. In this paper, we propose three block localization methods for improving mobile robot tracking and navigation performance. Unlike a conventional localization method, "the joint localization method" jointly estimates a block of successive locations of a robot imposing the constraint that** *the distances among the locations are exactly known for the robot.* **On the other hand, "the robot's location-assisted localization method" estimates the present location** *as if the previously estimated locations were those of anchor nodes*, **and "its iterative version" repeatedly updates all the locations** *changing the previously estimated locations.* **We discuss the performance of the three localization methods by computer simulation and an experiment.**

I. Introduction

Accurate localization is essential in successful mobile robot tracking and navigation. To this end, some have used camera [1], laser [2] and sonar [3] range finders at a mobile robot, and others have put RF-IDs [4] and access points [5] to surrounding environments. Several wireless data transmission standards such as the IEEE 802.11 (WiFi) and 802.15.4 (Zigbee) standards have been recently common, and anchor nodes based on these standards have been installed at the walls and ceilings in buildings and houses. Therefore, if accurate localization of a mobile robot can be provided by using these access points, we do not have to newly install devices specialized to mobile robot tracking and navigation. In this paper, we discuss a mobile robot localization with help of wireless access points. We call them "anchor nodes" in the following.

The physical layer protocols (PHYs) of the IEEE 802.15.4a [6] and 802.15.4f [7] standards are based on Ultra WideBand (UWB) technology, which supports accurate real-time ranging using time-of-arrival (TOA) measurement. However, the UWB technology has not been matured in the sense that the commercial devices are still expensive in markets. On the other hand, the IEEE 802.15.4 and 802.11 standards have the function of received signal strength (RSS) measurement applicable for ranging thus localization in their protocols, but the main drawback of the RSS ranging is its poor accuracy. Therefore, if we try to use RSS measurement for mobile robot tracking and navigation, it is essential to discuss how to improve the localization accuracy.

When we localize and track a man, we can use the behavior of man for improving the accuracy; for instance, we can use the human walking model [8] which is nonlinear to describe that a man cannot quickly change his direction. Applying the nonlinear human walking model in the state space representation of a particle filter, we can improve the accuracy of man tracking [9]. Furthermore, simply applying a low pass filtering for a man tracking, we can improve the accuracy [10]. This kind of nonlinear modeling and low pass filtering techniques may be applicable for the case of mobile robot, but one of the benefits of mobile robot's behavior is that *"it can quickly change the direction and speed anywhere and anytime,"* so much improvement in the localization accuracy by means of these techniques cannot be expected.

Let us discuss the difference on obtainable information between man walking and robot moving. For the case of man walking, he does not care about the speed of walking and the changes of directions he has made. For instance, when a man notices that he has stopped twice at different points, he does not know the distance between them. On the other hand, for the case of robot moving, of course, it does not know where it is in a given area, so it needs to estimate its own location; the estimated location includes an ambiguity, namely, an error. However, if the floor of the area is not slippery, it can exactly know the distances between any locations it has made and the directions it has changed, because it moves according to internal or external commands. Consequently, a man cannot obtain exact information on the distances between locations over which he has walked, whereas a robot can obtain it. Therefore, if the information on the known accurate moving distances is successfully applied in mobile robot localization, much improvement on its accuracy can be expected.

In this paper, to improve the localization accuracy in mobile robot tracking and navigation, we propose three methods, whose characteristics are as follows:

- The three methods estimate a block of successive locations which a robot has moved over.
- "The joint localization method" jointly estimates them, imposing the constraint that the distances among the locations are exactly known for the robot
- "The robot's location-assisted localization method" estimates the present location as if the previously estimated

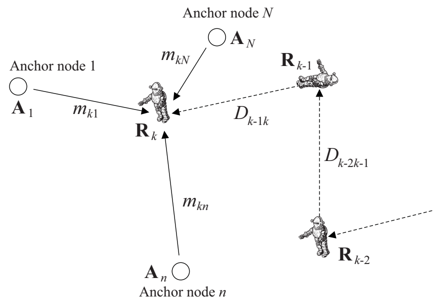

Fig. 1. System model.

locations in the block were those of anchor nodes

- "The iterative robot's location-assisted localization method" repeats the robot's location-assisted localization method to improve the accuracy of the presently and previously estimated locations.
- The three methods are based on maximum likelihood (ML) estimation, which are applicable for any localization methods such as TOA ranging-based and RSS ranging-based, so they are derived without specifying ranging methods.

Section II presents the models and problem statement. Section III describes the details on the proposed three localization methods, including a conventional ML localization method. Section IV demonstrates computer simulation and experimental results. Finally, Section V concludes the paper.

II. Models and problem statement

A. System model

Fig. 1 shows the system model, where there are N stationary anchor nodes and a moving robot in a given area. The known location of the nth anchor node ($n = 1, 2, \cdots, N$) and the unknown location of the robot at the kth time instant ($k = 0, 1, 2, \cdots$) are defined respectively as

$$\mathbf{A}_n = [X_n, Y_n] \quad (1)$$

$$\mathbf{R}_k = [x_k, y_k]. \quad (2)$$

The robot moves according to a series of commands on moving distances and directions, so if the area is not slippery, the robot can exactly calculate thus know the distances between any two different locations it has moved:

$$\begin{aligned} d^R(\mathbf{R}_{k'}, \mathbf{R}_{k''}) &= ||\mathbf{R}_{k'} - \mathbf{R}_{k''}|| = D_{k'k''} \\ (k', k'' &= 0, 1, 2, \cdots, k;\ k' < k'') \end{aligned} \quad (3)$$

where $D_{k'k''}$ is the known distance between the k'th and k''th locations.

B. Measurement model

The nth anchor node ($n = 1, 2, \cdots, N$) periodically sends a signal containing $\mathbf{A}_n$ to the robot, and using the received signal, the robot makes a measurement related to the distance between them. Here, we assume to know in advance the likelihood function, namely, the conditional probability density function *pdf* of the measurement as $p(m|d, \mu(d))$, where m, d and $\mu(d)$ are the measurement, the distance and the average of the measurement, respectively. For example, for the case of TOA measurement, we often assume the Gaussian function for the $p(m|d, \mu(d))$ [11]:

$$p(m|d, \mu(d)) = \frac{1}{\sqrt{2}\sigma} e^{-\frac{(m-\mu(d))^2}{2\sigma^2}} \quad (4)$$

$$\mu(d) = d/c \quad (5)$$

where σ and c are the standard deviation of the measurement error and the speed of the light, respectively. In addition, for the case of RSS measurment, we often assume the exponential distribution for the $p(m|d, \mu(d))$ [12]:

$$p(m|d, \mu(d)) = \frac{1}{\mu(d)} e^{-\frac{m}{\mu(d)}} \quad (6)$$

$$\mu(d) = \alpha d^{-\beta} \quad (7)$$

where α and β are constants, respectively.

C. Problem statement

At the kth location $\mathbf{R}_k$, the robot has obtained the measurement m_{kn} for the nth anchor node ($n = 1, 2, \cdots, N$) up to the present location. The log-likelihood function of $\mathbf{R}_k$ is written as

$$l_n(\mathbf{R}_k) = \log\ p(m_{kn}|d_n^A(\mathbf{R}_k), \mu(d_n^A(\mathbf{R}_k)) \quad (8)$$

where $d_n^A(\mathbf{R}_k)$ is the distance between the location of the kth location of the robot and that of the nth anchor node, which is given by

$$d^A(\mathbf{R}_k) = ||\mathbf{R}_k - \mathbf{A}_n||. \quad (9)$$

The localization problem is how accurately the robot estimates the kth location $\widehat{\mathbf{R}}_k$ using $l_n(\mathbf{R}_{k'})$ ($n = 1, 2, \cdots, N$, $k' = 0, 1, 2, \cdots, k$) and $d^R(\mathbf{R}_{k'}, \mathbf{R}_{k''}) = D_{k'k''}$ ($k', k'' = \cdots, -1, 0, 1, 2, \cdots, k;\ k' < k''$).

III. Localization methods

A. Conventional ML localization method

The kth location $\mathbf{R}_k$ can be independently estimated as the maximization problem:

$$\text{find } \mathbf{R}_k$$

$$\text{which maximizes } L(\mathbf{R}_k) = \sum_{n=1}^{N} l_n(\mathbf{R}_k).$$

There are a lot of algorithms for solving the above maximization problem having two variables. For instance, the conjugate gradient algorithm is applicable [13], but it should be noted that, to find the globally optimum location, several different initial locations are required, because this is a nonlinear maximization problem (without constraint). Every time when the robot has moved, it estimates the newly reached location regardless of the estimates of the previous locations.

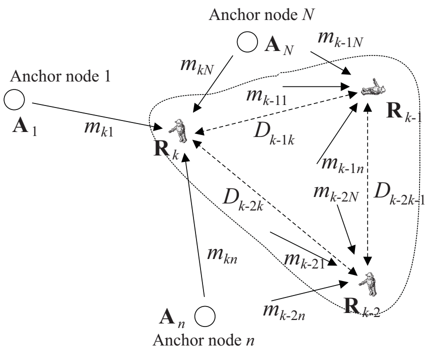

Fig. 2. Joint localization method for $J = 3$.

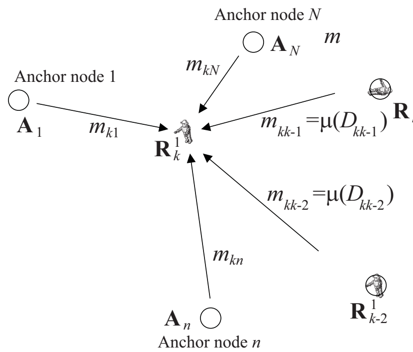

Fig. 3. Robot's location-assisted localization method for $J = 3$.

B. Joint localization method

A block of J locations $\mathbf{R}_{k-(J-1)}, \mathbf{R}_{k-(J-2)}, \cdots, \mathbf{R}_k$ can be jointly estimated as

$$\text{find a set of } \mathbf{R}_{k-(J-1)}, \mathbf{R}_{k-(J-2)}, \cdots, \mathbf{R}_k$$

$$\text{which maximizes}$$

$$L(\mathbf{R}_{k-(J-1)}, \mathbf{R}_{k-(J-2)}, \cdots, \mathbf{R}_k) = \sum_{j=0}^{J-1} L(\mathbf{R}_{k-j})$$

$$\text{subject to } d^R(\mathbf{R}_{k-j'}, \mathbf{R}_{k-j''}) = D_{k-j'k-j''}$$

$$(j', j'' = 0, 1, \cdots, J-1;\ j' < j'').$$

This a nonlinear maximization problem having $2J$ variables with nonlinear constraints, so the method of Lagrange multipliers is applicable [13]. The estimates of $\mathbf{R}_{k-(J-1)}, \mathbf{R}_{k-(J-2)}, \cdots, \mathbf{R}_{k-1}$ obtained when estimating the $(k-1)$th location are used as their initial values at the kth location and then they are all updated. In other words, the robot needs to store the estimates of the previous $J-1$ locations in its memory, when it moves.

Fig. 2 shows an example of the joint localization method for $J = 3$.

C. Robot's location-assisted localization method

Assume $\mathbf{R}_{k-(J-1)}, \mathbf{R}_{k-(J-2)}, \cdots, \mathbf{R}_{k-1}$ have been estimated and put the superscript 1 to them. The distances between $\mathbf{R}_k$ and $\mathbf{R}^1_{k-(J-1)}, \mathbf{R}^1_{k-(J-2)}, \cdots, \mathbf{R}^1_{k-1}$ are exactly known, so $\mathbf{R}_k$ can be estimated according to the following maximization problem:

$$\text{find } \mathbf{R}^1_k$$

$$\text{which maximizes } L(\mathbf{R}^1_k) = \sum_{n=1}^{N} l_n(\mathbf{R}^1_k)$$

$$\text{subject to } d^R(\mathbf{R}^1_k, \mathbf{R}^1_{k-j}) = D_{kk-j}$$

$$(j = 1, 2, \cdots, J-1).$$

Unfortunately, we found this method cannot work well, because the strict distance constraints propagate estimation errors from $\mathbf{R}^1_{k-(J-1)}, \mathbf{R}^1_{k-(J-2)}, \cdots, \mathbf{R}^1_{k-1}$ to $\mathbf{R}^1_k$, in other words, if one of $\mathbf{R}^1_{k-(J-1)}, \mathbf{R}^1_{k-(J-2)}, \cdots, \mathbf{R}^1_{k-1}$ contains a large estimation error, then $\mathbf{R}^1_k$ unavoidably contains a large estimation error. Therefore, we need to relax the distance constraints.

One idea is that we deal with $\mathbf{R}^1_{k-j}$ as if it were the location of an anchor node and the measurement between $\mathbf{R}^{(1)}_k$ and $\mathbf{R}^1_{k-j}$, namely, m_{kk-j}, were $\mu(D_{kk-j})$:

$$\text{find } \mathbf{R}^1_k$$

$$\text{which maximizes } \widetilde{L}(\mathbf{R}^1_k) = \sum_{n=1}^{N} l_n(\mathbf{R}^1_k) + \sum_{j=1}^{J-1} \widetilde{l}_j(\mathbf{R}^1_k)$$

$$\begin{aligned} \widetilde{l}_j(\mathbf{R}^1_k) \quad = \quad & \log p(\mu(D_{kk-j})| \\ & d^R(\mathbf{R}^1_k, \mathbf{R}^1_{k-j}), \mu(d^R(\mathbf{R}^1_k, \mathbf{R}^1_{k-j}))). \end{aligned}$$

This is a nonlinear maximization problem having two variables, and the robot also needs to store the estimates of the previous $J-1$ locations in its memory, when it moves.

Fig. 3 shows an example of the robot's location-assisted localization method for $J = 3$.

D. Iterative robot's location-assisted localization method

Once we use the robot's location-assisted localization method, we have $\mathbf{R}^1_{k-(J-1)}, \mathbf{R}^1_{k-(J-2)}, \cdots, \mathbf{R}^1_k$, so $\mathbf{R}^2_{k-j}$ $(j = J-1, J-2, \cdots, 0)$ can be estimated again using $\mathbf{R}^1_{k-j'}$ $(j' = J-1, J-2, \cdots, 0;\ j' \neq j)$. This estimation process can be repeated I times and the ith step is written as $(i = 2, 3, \cdots, I)$

$$\text{find } \mathbf{R}^i_{k-j}\ (j = J-1, J-2, \cdots, 0)$$

$$\text{which maximizes}$$

TABLE I
COMPUTER SIMULATION PARAMETERS

Field size	15m × 15m
Number of anchor nodes	3, 6, 9, and 14
Location of anchor nodes	random
Initial location of a robot	random
Moving distance	1m
Propagation constants	$\alpha = 2.36 \times 10^{-6}$ $\beta = 2.37$

$$\begin{aligned}
\widetilde{L}(\mathbf{R}^i_{k-j}) &= \sum_{n=1}^{N} l_n(\mathbf{R}^i_{k-j}) \\
&\quad + \sum_{\substack{j'=0 \\ j'<j}}^{J-1} \widetilde{l}^i_{j'}(\mathbf{R}^i_{k-j}) + \sum_{\substack{j'=0 \\ j'>j}}^{J-1} \widetilde{l}^{i-1}_{j'}(\mathbf{R}^i_{k-j}) \\
\widetilde{l}^i_{j'}(\mathbf{R}^i_{k-j}) &= \log p(\mu(D_{k-jk-j'})| \\
&\quad d^R(\mathbf{R}^i_{k-j}, \mathbf{R}^i_{k-j'}), \mu(d^R(\mathbf{R}^i_{k-j}, \mathbf{R}^i_{k-j'}))) \\
\widetilde{l}^{i-1}_{j'}(\mathbf{R}^i_{k-j}) &= \log p(\mu(D_{k-jk-j'})| \\
&\quad d^R(\mathbf{R}^i_{k-j}, \mathbf{R}^{i-1}_{k-j'}), \mu(d^R(\mathbf{R}^i_{k-j}, \mathbf{R}^{i-1}_{k-j'}))).
\end{aligned}$$

Note that, when estimating the present location ($\mathbf{R}^i_{k-j}$), the previous locations ($\mathbf{R}^i_{k-(J-1)}$, $\mathbf{R}^i_{k-(J-2)}, \cdots, \mathbf{R}^i_{k-(J-(j-1))}$) have been estimated and then updated. This requires a memory for the estimates of the previous $J-1$ locations and an iterative process in the algorithm, but it is a nonlinear maximization problem having two variables.

Fig. 4 shows an example of the iterative robot's location-assisted localization method with $i = 2$ for $J = 3$.

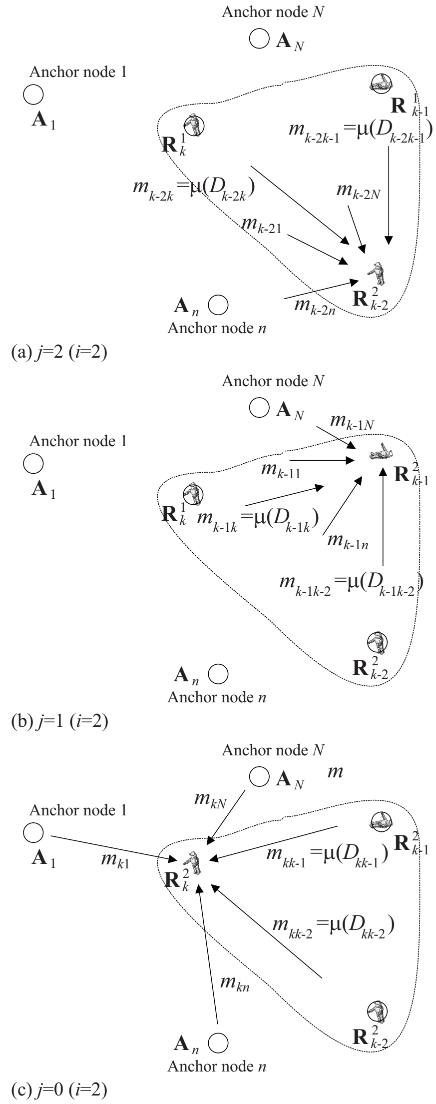

Fig. 4. Iterative robot's location-assisted localization method for $J = 3$.

IV. PERFORMANCE EVALUATION

A. Computer simulation results

We measured the RSSI for the IEEE 802.15.4 signal in a room of our university and confirmed that its *pdf* is exactly the exponential distribution given by (6) and (7), and based on the measurement data, we determined the computer simulation setup, whose parameters are shown in Table I.

In the computer simulation, at the kth location, a robot receives Q packets ($q = 1, 2, \cdots, Q$) from each anchor node. The RSSIs are assumed to be uncorrelated among the packets, and every time the robot receives a packet from the nth anchor node, it calculates the average RSSI and estimates its own location. Defining the qth RSSI for the packet from the nth anchor node at the kth location as $RSSI^q_{kn}$, the measurement up to the q'th packet is written as

$$m_{kn} = m^{q'}_{kn} = \frac{1}{q'} \sum_{q=1}^{q'} RSSI^q_{kn} \tag{10}$$

so the measurement approaches to the true average as the number of packets increases.

Fig. 5 shows the convergence process of the localization error for the conventional ML localization method (conventional), joint localization method (joint) using J=3, robot's location-assisted localization method (assisted) using J=3 and iterative robot's location-assisted localization method (iterative) using J=3 and I=3. Here, a robot moves three times from an initial ($k = 0$) location to the third ($k = 3$) location through the first ($k = 1$) and second ($k = 2$) locations and every time when it moves, it receives 30 packets (Q=30). Note that, to localize the three locations, the estimated of the initial location ($k = 0$) is not used and the total number of packets from the first location is counted in the figure. For the conventional method, each of the locations is always independently estimated, on the other hand, for the remaining three methods, the first location ($k = 1$) is estimated according to the conventional method (because they can get the RSSI information only for the location), and the second location ($k = 2$) is estimated according to the corresponding methods using $J = 2$. At each location, as the number of received packet increases, the performances of all the four methods improve, because the measurement approaches to the true

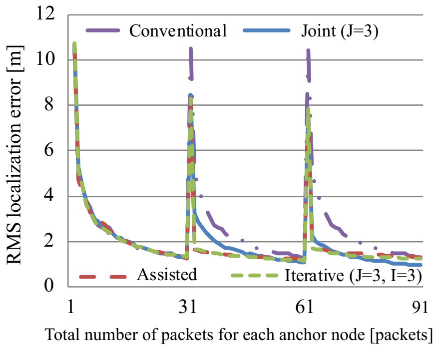

Fig. 5. Convegence process of the RMS localization error.

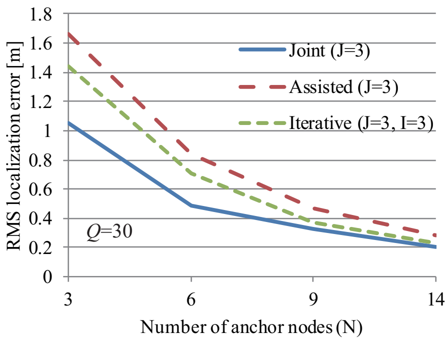

Fig. 6. RMS localization error versus the number of anchor nodes.

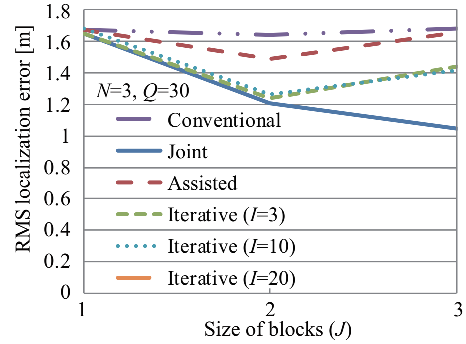

Fig. 7. RMS localization error versus the size of blocks.

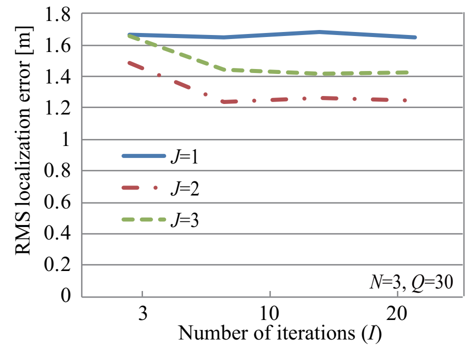

Fig. 8. RMS localization error versus the number of iterations for the iterative robot's location-assisted localization method.

average. The convergences of the assisted method and the iterative method are faster than the convergence of the joint method, but the irreducible RMS localization error of the joint method is the smallest at Q=30. The performance of the iterative method is better than that of the assisted method.

Fig. 6 shows the dependency of the root mean square (RMS) localization error on the number of anchor nodes for the joint, assisted and iterative methods. As the number of anchor nodes increases, the performances of the three methods improve. The joint method is more effective when the number of anchor nodes is smaller; as the number of anchor nodes increases, the advantage of the joint method over the assisted and iterative methods diminishes, still keeping a slightly better performance over the two methods.

Fig. 7 shows the dependency of the RMS localization error on the size of blocks. For the joint method, as the size of blocks increases, the RMS localization error monotonously improves, so setting a larger size of blocks is advantageous, although it becomes more computationally intensive. On the other hand, for the assisted and iterative methods, the block size of two ($J = 2$) gives the smallest RMS localization error. This may be because setting the size of blocks more than three increases the localization errors propagated from the previously estimated locations.

Fig. 8 shows the dependency of the RMS localization error on the number of iterations for the iterative method. For all the sizes of blocks, the iteration number of ten is sufficient enough to improve the RMS localization error.

Consequently, from the results of Figs. 7 and 8, we set $J = 2$ for the assisted and iterative methods whereas we set $I = 10$ for the iterative method.

B. Experimental results

We conducted an experiment using a robot [14] in a stadium (35.1m $\times$ 19.0m). First of all, by a pre-measurement, we obtained the propagation constants as $\alpha = 8.9 \times 10^{-7}$ and $\beta = 1.12$. Fig. 9 shows a picture of the robot. It is equipped with a palm-top personal computer (PC) for executing the localization algorithms and a MICA-Z node as a wireless communication tool.

In the stadium, we localized the robot in the area of 15m $\times$ 15m, where we put nine MICA-Z nodes as anchor nodes. Fig. 10 and Table II show the area layout and the parameter setting for the experiment, respectively.

Fig. 11 shows the convergence of the localization error. Here, from the computer simulation results obtained in the previous section, we set $J = 2$ for the assisted and iterative methods and $I = 10$ for the iterative method whereas we set $J = 3$ for the joint method. Against our expectation, the performance was not always improved as the number of packets increases, and furthermore, the performances of the joint and iterative methods, are worse, and the performance of

Fig. 9. A picture of the robot.

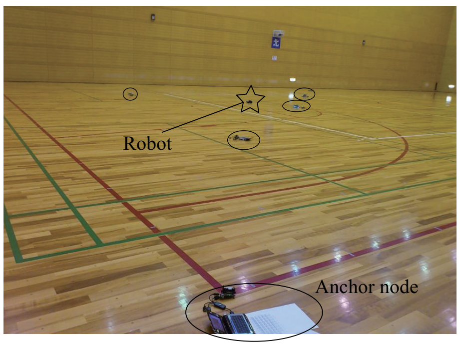

Fig. 10. Localization area layout.

the assisted method is the best. Now, we are investigating the reason, but it may be because:

1) The channel state in the experiment was rather static, so even as the number of packets increases, the average RSSI did not approached to the true average
2) The localization error was too larger, so taking the previous location into consideration worsened the performance of localizing the present location; this effect is more true for the joint method with the strict constraint on the distances between the locations, so the joint method performed worse; the assisted and iterative methods have the relaxed constraint, so they performed better, but the iterative method magnified the localization error in the iteration process.

V. Conclusions

In this paper, we have discussed the three block localization methods for improving mobile robot tracking and navigation performance, such as joint, assisted and iterative methods. The assisted method does not always performs best among the three in the computer simulation, whereas it performs best in the experiment. It simply estimates the present location as if the "just-one-previous" location were that of an anchor node.

Acknowledgement

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TABLE II
Experimental Parameters

Field size	15m × 15m
Number of anchor nodes	9
Location of anchor nodes	(0,0),(15,0),(0,15), (15,15),(7.5,7.5),(3.75,3.75), (11.25,3.75),(3.75,11.25),(11.25,11.25)
Initial location of a robot	random
Moving distance	1m
Propagation constants	$\alpha = 8.9 \times 10^{-7}$ $\beta = 1.12$

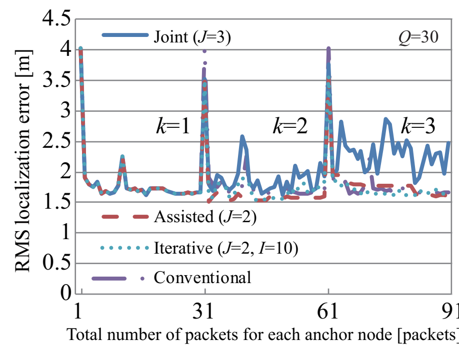

Fig. 11. Convergence process in the experiment.

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