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Pose Estimation of a Mobile Robot on a Lattice of RFID Tags

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***Abstract*— A method of estimating pose of a robot on a lattice of RFID tags is described. In recent years, radio frequency identification (RFID) technology has become a very popular method for localizing robots because it is robust to disturbances such as lighting and obstacles, which adversely affect the conventional methods that use cameras, supersonic waves and so on. Despite the advantage that RFID tags, especially passive tags, can be inexpensively mass-produced, previous studies using RFID have not targeted the detailed work of robots because they have made use of RFID tags dotted over a wide area as landmarks. Therefore, it is still difficult to use the technology at home. There is a model room in WABOT-HOUSE Laboratory of Waseda University where the floor is equipped with a lattice of RFID tags at 300mm intervals, simulating a future home environment where robots interact symbiotically with humans. We speculate that such an environment, where the tags are distributed at regular intervals, is one of the most probable infrastructures of the near future and propose a method that use Monte Carlo localization to estimate the pose of robot on the lattice. Our experiments show that robots can localize their position more precisely than the interval of tags and also estimate their orientation successfully by using the proposed method when two readers are placed in appropriate positions.**

I. INTRODUCTION

In recent years, RFID technology has become very popular among various fields of our life against a background that they came to be mass-produced inexpensively. Moreover, RFID has robustness to disturbances such as lighting and obstacles, sparking research interest in the field of robot navigation. They are two kinds of RFID systems: one uses RFID readers, which emit electric waves: the other uses IC tags, which contain circuitry and send their unique identifiers to readers using power from radio waves. IC tags can play the role of landmarks for a robot moving by referring to a table that lists IC tag codes and the global position.

In our laboratory, there is a model room called "the Human and Robot Symbiotic Space for Near-term Future Living" where many RFID tags are installed to estimate a robot's state[1][2]. We speculated that a lattice of RFID tags under the floor in our model room is an information infrastructure prototype that will be further developed in the near future and investigated how robots can determine their pose on such floors. We first developed a measurement likelihood model to make use of the discrete information from RFID tags in the probabilistic framework and proposed a method of localizing the pose of a robot using Monte Carlo localization. Finally, to test the effectiveness of the model, we recorded errors in position and orientation predicted using forward and rotating motion of robots with different reader arrangements. The experiment showed, when two readers are placed in appropriate positions, the average position error by rotating motion is about 5 cm and the average position error by forward motion is about 10 cm, which are much smaller than the RFID tag's interval (=30 cm). Besides, robots can localize their orientation in the range of 0.1rad. The experiment also produced important guidelines for reader configurations.

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This paper is organized as follows. We describe related work on localization using RFID technology and discuss our study's place in the literature in Section II. We explain how the RFID technology was installed in our laboratory in Section III. In Section IV, we describe the sensor model that represents the relation between robot's pose and detection of RFID signal and present the Monte Carlo localization prediction method. In Section V, we present our experimental results, and conclude the paper in Section VI.

II. RELATED WORK

Studies about localizing robots with RFID technology can be divided into two different approaches. In one approach, the position of the IC tags are known, and, in the other, they are not.

Hähnel et al. proposed a probabilistic sensor model that uses the relation between frequencies to detect IC tag and robot's state and learns the mapping of IC tag via a laser-based SLAM algorithm when the IC tag positions are unknown[3]. Schneegans took the "snapshots" to learn a relation between detected signals and a robot's state and a robot's state and estimated to localize itself[4]. Such approaches require some measurements depending on the environment to be able to map the IC tags' positions in advance. Yamano et al. used a support vector machine to estimate the position of a robot based on signal strength when active tags are distributed in unknown positions[5]. This approach also needs to collect learning data every time the arrangement of the IC tags is changed. Their assumption that the position of IC tags are unknown is based on the consideration that it is not realistic for users to arrange RFID tags in a space efficient manner or to identify and input the location of every tag. However, such a problem will be disappeared if the environment , where the RFID tags are installed in a distributed manner, is prepared inexpensively when a room is constructed. Such an arrangement of infrastructure can be rapidly developed when there is a general need to live symbiotically with robots. So we think it is an enough probable precondition that the position of IC tags are known.

Most previous studies based on the precondition that the position of IC tags are known use an IC tag antenna with wide signal reception ranges comparatively, so they cannot accurately locate the robot or its orientation[6][7]. Therefore, it is still risky to use the technology at general home environment. Park et al. proposed a method of moving to the objective position autonomically while estimating a robot's pose when the floor is equipped with a lattice of IC tags (HF, 13.56MHz, 76 mm*45 mm) at 34 cm intervals, which is very similar to our configuration[8]. They use an antenna with a diameter of about the IC tag's interval, so the position cannot be specified more precisely than the interval. Furthermore, forward motion must be performed during a certain distance to estimate its orientation. Asakawa et al. succeeded in locating a robot on the floor, which is equipped with the few rows of tags, more precisely than the interval by taking the timing when tags are detected[9]. However, a fixed rotating operation is required at a fixed field.

We think an environment with a lattice of RFID tags in the floor is one of the most probable information infrastructures for simultaneously localizing a robot's position more precisely than the interval of the IC tags and estimation its orientation. Especially, we aim to estimate a robot's pose using only rotating motion, that is, when the robot's position is not changing. It is very risky for a robot to start to move without knowing where it is a home. Therefore, it is very useful to localize a robot's pose at the same place, especially when the robot is operating in a small space or when a robot must enter a battery-charging station.

III. OUR RFID TECHNOLOGY

As shown in Figure 1, which is a photograph taken during construction, the floor is equipped with about 350 RFID lattice-shaped tags, each of which is a square, 260-mm on a side (Hitach Industrial Equipment System) , at 300-mm intervals. Robots are not affected by the obstacle between the readers (Figure 2, Hitachi Industrial Equipment System) and tags because they are very closer by installing them the base of the robot. Fifteen-mm-high wooden boards are laid on the tags to avoid a partial impact at the area of the circuitry. Since the tags are passive tags, which last as long as the house, they do not need to be replaced, The IC tags can be used even when the floor gets wet since they operate in the low frequency band (LF, 125KHz).

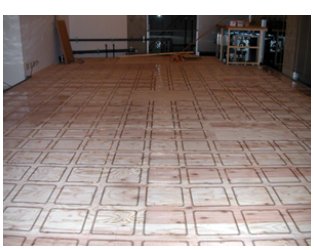

Fig. 1. RFID Lattice-shaped Tags (During Construction).

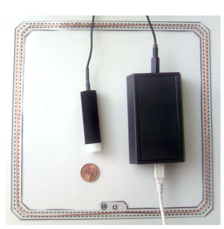

Fig. 2. A RFID Reader.

We used large IC tags than those used in previous studies. Tags smaller than the desired accuracy could not be efficiently and evenly arranged throughout the room. When the floor is dotted with tags, however, a robot equipped with a small reader antenna cannot always transmit the signal to the tags. By using larger tags, the robot can acquire signals irrespective of its position. However, the resolution of position data from such tags decreases, making it impossible to accurately locate the robot. We propose a method of solving this problem in the next section.

IV. LOCALIZATION

Our reader cannot detect more than a single IC tag in a single measurement. Therefore, the robot must be equipped with multiple readers or make use of the history of motor and sensor signal to localize its position more accurately than the intervals between tags. We used Monte Carlo localization[10], which is a method of localizing robots using a particle filter that estimates the most probable state in light of past history. The sensor model of RFID readers in our environment is geometrical, so it cannot be represented in a linear expression. That is, it is an appropriate selection to use a non-parametric probabilistic model particle filter.

Let $X_t = [x_t, y_t, \theta_t]^T$ be the robot's state vector at time t, and u_t and $Z_t$be the vector of the control signal and the sensor signal at time t, respectively. The following steps are repeated to generate samples proportional to the distribution of $p(X_t|Z_{1:t}, u_{1:t})$.

1) Update particles by prediction using $P(X_t|u_t, X_{t-1})$.
2) Update particles by correction using sensor model.
    a) Update weight particles using $P(Z_t|X_t)$.
    b) Mix random particles using $p(X_t|Z_t)$.
    c) Update the particles by resampling.

Along among these processes, $p(X_t|u_t, X_{t-1})$, which represents the control model of robot, can be calculated using odometry. Resampling is done using low variance resamplig after normalizing the weight of the particles. We describe the method of updating the weight of the particle and mixing random particles below.

A. Weight Updating Model

A lth particle consists of $X_t^{(l)}$, which represents the hypothesis of each particle's current pose, and $w_t^{(l)}$, which represents weight proportional to the distribution of $P(Z_t|X_t^{(l)})$. Here, we set the precondition that "no detection" events Z_t provide no information to the sensor model of the RFID reader. This is because we cannot distinguish between the following phenomenon already as pointed out by Hähnel[3],

1) A reader cannot detect because it is out of the tag's detection range (*false-positive readings*).
2) A reader cannot detect because the tag cannot sense the signal although it is in the vicinity of the antenna (*false-negative readings*).

Some likelihood models can be obtained by measuring the above two conditions, but such approaches depend on the characteristics of the reader of tag. Therefore, we assume that the probability of "no detection" event is constantly distributed, that is, weight $w_t^{(l)}$ is evenly distributed among all particles. In the following equation, we approximate the posterior $P(Z_t|X_t)$ for cases in which one or more tags are detected, that is, $Z_t \neq \phi$.

Let $\bar{X}_t = [x_y, y_t]^T, \theta_t$ be position vector and orientation value of a robot at time t and L_{R_i}, θ_{R_i} be the distance from the origin and the angle of ith reader in the robot's coordinate [1]. $\bar{X}_{R_i,t}$, which represents the ith reader's position vector in the global coordinate, is calculated as follows.

$$\bar{X}_{R_i,t} = \bar{X}_t + \begin{bmatrix} \cos\theta_t & -\sin\theta_t \\ \sin\theta_t & \cos\theta_t \end{bmatrix} \begin{bmatrix} L_{R_i}\cos\theta_{R_i} \\ L_{R_i}\sin\theta_{R_i} \end{bmatrix} \quad (1)$$

Here, we approximate the posterior probability of measurement of $tag_{n_i,t}$ detected by the ith reader as follows,

$$P(tag_{n_i,t}|X_t) = Sg(D(tag_{n_i,t}, \bar{X}_{R_i,t})) \quad (2)$$

$$Sg(l) = \frac{2}{1+\exp^{\lambda l/L}} \quad (3)$$

where L denotes the tag's width, and $D(tag_{n_i,t}, \bar{X}_{R_i,t})$ represents the distance from the edge of the tag to the ith reader (which returns 0 if it is within the tag's space), and $Sg(l)$ is a discrete sigmoid function. Figure 3 shows the posterior $P(Z_t = \{tag_{n_i,t}\}|\bar{X}_{R_i,t})$ when normalizing the width and the origin of tag ($\lambda = 50$). As shown in the Figure 3, the probability changes rapidly on the boundary side of the tag since the area of the detection is almost same as that of the existence area of the tag.

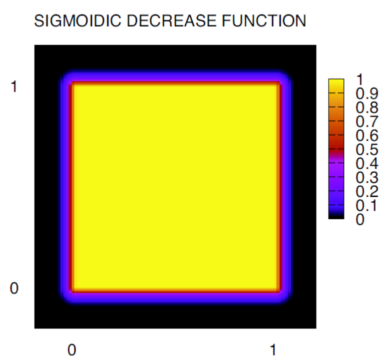

Fig. 3. Decrease Sigmoid Function.

Assuming that the measurements of the reader's detection are independent, the resulting likelihood function is calculated as follows.

$$P(Z_t = \{tag_{n_i,t}\}|X_t) = \prod_i P(tag_{n_i,t}|X_t) \quad (4)$$

B. Mix with Random Particles

Our sensor model of the RFID reader has a sigmoid (discrete) characteristic, so "particle depletion" , which means the situation in which all particles move to the area of low likelihood and cannot restore the correct state, can be caused easily if the control model works not well[11]. For more robust prediction, we replace the "bad" particles, which have lower weight than ϵ, with random particles proportional to the distribution of $P(X_t|Z_t)$ in the following step.

1) generate the particles, each of which has the hypothesis of the ith reader's position denoted as $\bar{X}_{R_i}^{(m)}$ proportional to the $P(\bar{X}_{R_i,t}|Z_t)$.
2) give each particle orientation denoted as $\theta_{R_i*}^{(m)}$ from the possible area at random.
3) translate to the state of robot, $\bar{X}^{(m)}, \theta^{(m)}$.

In the following, we explain situations in which there is a total of one or two detected tags. Here, we skip the denotation of time t in order to simplify the expression.

1) Single Tag is Detected: Let Z be $\{tag_{n_p}\}$ and offset position of tag_{n_p} be $[\alpha_{n_p}, \beta_{n_p}]^T$. $P(\bar{X}_{R_p}|Z = \{tag_{n_p}\})$ is constantly distributed inside the detected tag, so the particle of the pth reader's state is generated as follows.

$$\bar{X}_{R_p}^{(m)} = \begin{bmatrix} \alpha_{n_p} \\ \beta_{n_p} \end{bmatrix} + \begin{bmatrix} rand(0,L) \\ rand(0,L) \end{bmatrix} \quad (5)$$

$$\theta_{R_{po}}^{(m)} = rand(-\pi, \pi) \quad (6)$$

Here, $\theta_{R_{po}}^{(m)}$ represents the orientation of the robot in relation to the pth reader, and $rand(a,b)$ is a function that generates random numbers from the constant distribution from a to b. Finally, the reader's pose hypothesis is transformed into the robot's pose hypothesis.

$$\bar{X}^{(m)} = \bar{X}_{R_p}^{(m)} + L_{R_p} \begin{bmatrix} \cos(\theta_{R_{po}}^{(m)}) \\ \sin(\theta_{R_{po}}^{(m)}) \end{bmatrix} \quad (7)$$

$$\theta^{(m)} = \pi + \theta_{R_{Po}}^{(m)} - \theta_{R_p} \quad (8)$$

2) Two Tags are Detected: Let Z be $\{tag_{n_p}, tag_{n_q}\}$. In the following, we describe how to obtain the posterior $P(\bar{X}_{R_p}|Z)$ of the pth reader's position. Here, for simplicity, we treat the case of $\alpha_{n_q} >= \alpha_{n_p} + L$ (an appropriate geometric transformation will enable other situations to the same equations). When the pth reader's position is fixed, orientation range $\dot{\Theta}(\bar{X}_{R_p}, \alpha_{n_q}, \beta_{n_q})$, where the qth reader is included in the L-shaped space that consists of $x = \alpha_{n_q}$ and $y = \beta_{n_q}$, is

$$\theta_\alpha = acos\{(\alpha_{n_q} - x_{R_p})/L_{pq}\}$$

$$\theta_\beta = asin\{(\beta_{n_q} - y_{R_p})/L_{pq}\}$$

$$\dot{\Theta}(\bar{X}_{R_p}, \alpha_{n_q}, \beta_{n_q}) = \begin{cases} 2\theta_\alpha & (\theta_\beta \leq -\theta_\alpha) \\ \theta_\alpha - \theta_\beta & (|\theta_\beta| \leq \theta_\alpha) \\ 0 & otherwise \end{cases} \quad (9)$$

where L_{pq} denotes the distance between the readers. Therefore, the orientation range, in which the qth reader is included in the square space consists of $x = \alpha_{n_q}, \alpha_{n_q}+1, y = \beta_{n_q}, \beta_{n_q}+1$, is calculated as follows.

$$\Theta(\bar{X}_{R_p}, tag_{n_q}) = \tilde{\Theta}_{0,0} - \tilde{\Theta}_{L,0} - \tilde{\Theta}_{0,L} + \tilde{\Theta}_{L,L} \quad (10)$$

$$\tilde{\Theta}_{x,y} = \dot{\Theta}(\bar{X}_{R_p}, \alpha_{n_q}+x, \beta_{n_q}+y) \quad (11)$$

[1] X represent three-dimensional vector including the orientation and $\bar{X}$ represent two-dimensional position vector.

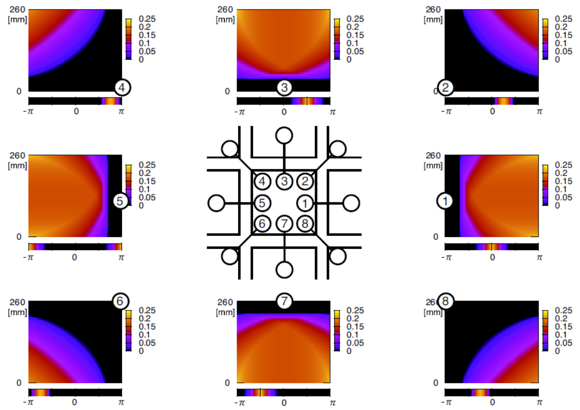

Fig. 4. Probability distribution of one reader's pose when two tags are detected side by side ($P(Z|\bar{X}_{R_p}), P(Z|\theta_{R_{pq}})$). Layout of each figure represents the relation between their positions.

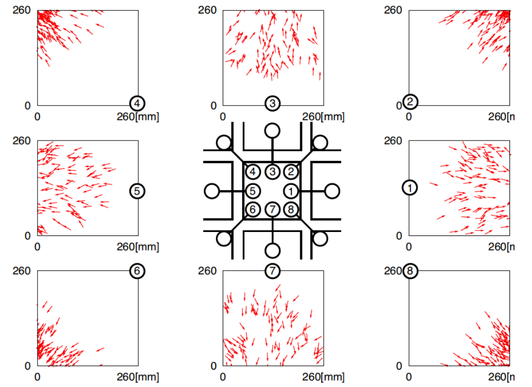

Fig. 5. Generated 100 random particles in condition corresponding to that shown Fig. 5 ($n_{rp} = 3$).

Finally, when $\alpha_{n_p} + L$,

$$P(Z = \{tag_{n_p}, tag_{n_q}\}|\bar{X}_{R_P}) = \Theta(\bar{X}_{R_p}, tag_{n_q})/2\pi \quad (12)$$

Eq. 12 is transformed according to Bayes' rule.

$$P(\bar{X}_{R_p}|Z) = \eta P(Z|\bar{X}_{R_p})P(\bar{X}_{R_p}) \quad (13)$$

Here, hypotheses of the pth reader's position should be generated proportional to the Eq. 12 since η and $P(\bar{X}_{R_p})$ are constant values.

The sampling procedure is implemented as follows.

1) generate initial particles of the pth reader's position at random inside tag_{n_p}.
2) add slightly random noise to the particle (since two turns).
3) calculate the weight according to Eq. 12.
4) resample using low variance resampling.
5) repeat step 2 to 4 n_{r_p} times.

$\theta^{(m)}_{R_{pq}}$, the orientation of the position of the pth reader relative to that of the qth reader, is generated at random from the approximately determined possible orientation area.

$$\begin{aligned}
\theta_- &= \max(acos\frac{\alpha_{n_q} + L - x^{(m)}_{R_p}}{L_{pq}}, asin\frac{\beta_{n_q} - y^{(m)}_{R_p}}{L_{pq}}) \\
\theta_+ &= \min(acos\frac{\alpha_{n_q} - x^{(m)}_{R_p}}{L_{pq}}, asin\frac{\beta_{n_q} + L - y^{(m)}_{R_p}}{L_{pq}}) \\
\theta^{(m)}_{R_{pq}} &= rand(\theta_-, \theta_+) \quad (14)
\end{aligned}$$

Finally, the robot's position and orientation is

$$\bar{X}^{(m)} = \bar{X}^{(m)}_{R_p} + L_{r_p}\begin{bmatrix} \cos(\theta^{(m)}_{R_p} - \theta_{opq}) \\ \sin(\theta^{(m)}_{R_p} - \theta_{opq}) \end{bmatrix} \quad (15)$$

$$\theta^{(m)} = \pi + \theta^{(m)}_{R_{pq}} - \theta_{R_p} - \theta_{opq} \quad (16)$$

where θ_{opq} denotes $\angle OPQ$ [2]. Figure 4 shows $P(Z|\bar{X}_{R_p})$ and $P(Z|\theta_{R_{pq}})$ [3] when two readers whose distance is $L_{pq} = 300$ mm detect tags side by side under the same conditions as in the model room, that is, $L = 260$ mm and the intervals between tags are 300 mm. We can see that the precision of the estimation of the robot's position and orientation improves when two RFID tags are detected at the same time. Figure 5 shows the results for the method mentioned above and generating 100 random particles under the conditions shown in Fig. 4. It can be seen that they successfully approximate the actual probability distribution. Random particles are also generated when initializing the particle, that is, the prediction starts after RFID tags of one or more are detected.

[2] O, P, Q each represents the position of robot and two readers.

[3] derivation of the equation is omitted here.

V. EXPERIMENT

A. Experimental Design

We did an experiment to test the effectiveness of our method. To measure the robot's position accurately, we arranged nine of the same type of RFID tags as are used in the model room on the floor at uniform intervals (30 cm) in a lattice and affixed them with transparent tape. Figure 6 shows the experimental environment and the bottom half of the robot named WGH2.

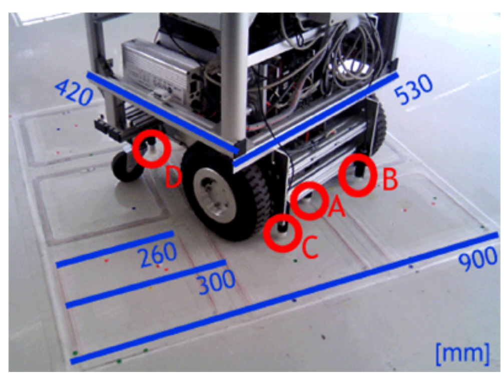

Fig. 6. Experimental environment and WGH2

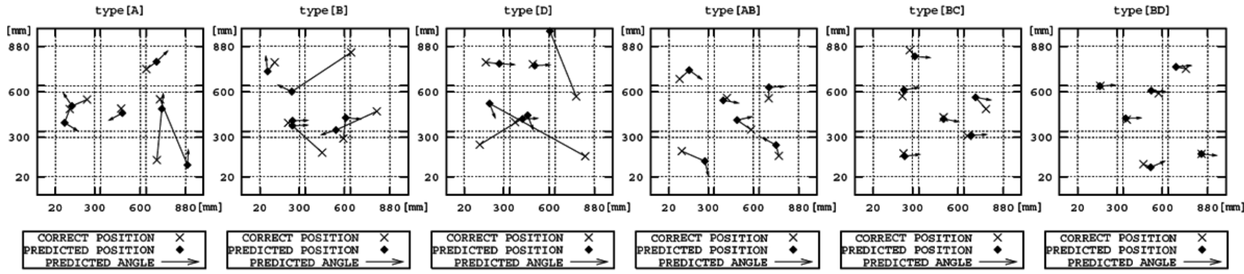

Fig. 7. Predicted pose and actual stop position by rotating motion

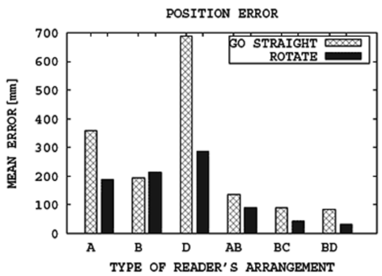

Fig. 8. Position error

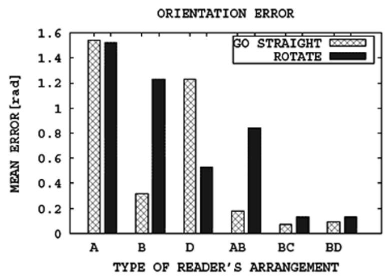

Fig. 9. Orientation error

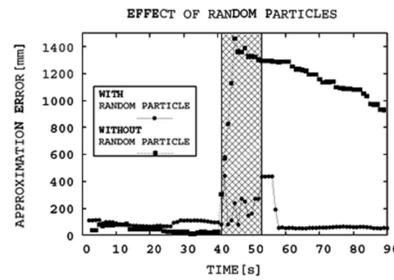

Fig. 10. Effect of random particles

The robot has an encoder that monitors its rotation and can be equipped with the RFID readers in four places. We installed either one or two readers depending on the experiment. The distance [mm] and direction [rad] of the position of four RFID reader's from the origin of the robot's coordinates are $(L_{R_A}, \theta_{R_A}) = (60, 0)$, $(L_{R_B}, \theta_{R_B}) = (170, 0.92)$, $(L_{R_C}, \theta_{R_C}) = (170, -0.92)$, and $(L_{R_D}, \theta_{R_D}) = (340, -2.78)$. Here, the subscripts A, B, C, and D correspond to their places in the figure. The robot has a table that lists tag IDs and the offset position.

We did two kinds of experiments in the environment descried above. Hereafter, we refer to the square area where nine tags are arranged as the tag area. Six kinds of reader arrangements (A, B, D, AB, BC, and BD) were used in each experiment.

1) We randomly selected a place in the tag area and rotated the robot five times at the position (about 23 sec per rotation) then stopped the robot toward X-axis positive direction. Then the predicted position and orientation and the stop position is recorded. This was repeated six times for every arrangement pattern.
2) The robot first went forward in the tag area from outside of the tag area to the opposite then came back, and then went forward (about 0.25km/h). Then we stopped the robot as it turned in the X-axis positive direction and recorded the predicted position, orientation and stop position. This was repeated three times each for the motions parallel and diagonal to the row of tags, for a total of six times for each arrangement pattern.

The experiments were done using 50 particles and with $\lambda = 50, \epsilon = 0.01, n_{rp} = 3$, and the particles were updated every second.

B. Experimental Results

Figure 7 shows the stop position after rotation and Figure 8 and 9, respectively, show the average position and orientation errors for rotating motion and forward motion for the six reader arrangements.

It can be seen that the predictions by single reader generally have larger localization errors than those by two readers. The orientation error is especially high for the A arrangement. Since reader A is very close to the center of the robot's rotation (that is, the origin of robot's coordinate), the orientation information cannot be effectively utilized in Eq. 1 (clues to identifying orientation are lost when the position of a reader corresponds to the origin). The reason why AB's localization error is larger than order arrangements with two readers may be due to the small contribution of reader A. D's reader position error is larger than the others. Figure 7 shows that there are cases of successful convergence and of serious error. Analyzing the experimental data, we found cases where particles of wrong hypothesis survived and where random particles did not work well. Since reader D is far from the origin of the robot coordinate, the hypothesized distribution of the robot's pose was widely distributed in Eq. 1. This may cause the robot to continue to have the wrong assumption. When the wrong assumption has disappeared and a new assumption is mixed using random particles, the robot cannot specify particles in the narrow area for the same reason as in Eq. 6. Therefore, relatively many particles are needed when one reader that is far from the origin of robot is used.

It can be seen that using two readers other than AB results in accurate prediction. Almost all of the orientation error is lower than about 0.1 rad. The difference between the position errors for forward motion is a little high because there are some trials of motion parallel to the row of tags in which the error is more than 10cm. The error of trial of motion diagonal to the row of tags is generally less than 10cm. On the other hand, the errors are much lower than those for the interval of tags, so there results show that the proposed method is effective. The highly accurate estimation of rotating motion may be due to the rich combination of tags that can be detected.

These results show that our method enables the robot to estimate its position and orientation more accurately than the tag intervals when the readers are appropriately arranged. The following items should be considered when RFID readers are configured.

1) A reader should not be placed near the center of robot's rotation.
2) The number of particles should be considered when a reader is placed far from the center of the robot's rotation.
3) Rotating motion can be estimated more accurately than forward motion.
4) Two readers can estimate the pose much more accurately than a single reader.

C. Effect of Random Particles

To test the effect of random particles, we intentionally add encoder's turbulence while the robot is rotating and compared the difference based on the presence of random particles (Figure 9). The reader arrangement used in the experiment was BC.

The vertical axis of the figure represents the distance from the robot's final position, that is, it represents an approximation of the localizing error. For 40-50 seconds when given the turbulence, the position error of the particle with no random particles keeps rising and returns to the correct answer very gradually after the turbulence, which was caused by the design of a steep sigmoid function. In contrast, the error with random particles does not fall into disorder greatly during given the turbulence and rapidly converges to the correct area after that. The results of this simulation show that random particles enable robust prediction to the performance of the control system.

VI. CONCLUSION

We proposed a method that uses the Monte Carlo algorithm to estimate the pose of a robot on a lattice of RFID tags. When two readers are placed appropriately with a low number of particles, orientation error converges at the very small error of about 0.1 rad and position error converges on an estimated position much smaller than the tag interval (about 5 cm for rotating motion and about 10 cm for forward motion). Such high accuracy may help the robot when it needs to make very precise movements such as entering a battery station. It is possible that because of its simplicity, low cost, robustness and performance, the environment (a floor equipped with a lattice of RFID tags) can be used as infrastructure in homes and offices.

Finally, we metion two points that we plan to study in future work.

1) We will examine how to check the reliability of the current prediction. This will enable us to formulate a new method of planning behavior, for example, such that the robot starts moving after rotating and converging on high reliability.
2) We confirmed that localizing accuracy depends on what trajectory the readers draw though the problem is not referred especially above. The fact implies that the robot can get more accurate estimation by shifting the moving-line slightly even if the robot is in the "dead point". We will develop an algorithm for escaping from the dead point and localizing the pose more robustly.

VII. ACKNOWLEDGMENTS

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