Performance analysis of mobile robot self-localization based on different configurations of RFID system

Performance Analysis of Mobile Robot Self-Localization based on Different Configurations of RFID System

Jian Mi[1] and Yasutake Takahashi[1]

***Abstract*— This paper analyzes the MCL (Monte Carlo Localization) performances of an omnidirectional vehicle based on an RFID system with multiple readers at the bottom of a vehicle and the tags on the floor with different configurations of RFID system. This paper also proposes a method of reinitializing of the particles in the MCL and a likelihood function as the measurement model that are specialized to the RFID based self-localization. The simulations demonstrate that how accurately the self-localization works according to the changes of the RFID system's configuration and how the definition of the likelihood function affects the accuracy. The results show that the self-localization based on MCL works accurately enough for realistic situation even using less RFID readers on the vehicle and lower density IC tag textiles on the floor.**

I. INTRODUCTION

Conventional methods using vision sensors and/or laser range finders for indoor autonomous robot self-localization are not robust against the changes of environment. Transparent walls, which are popularly used in houses and hospitals for example, make it difficult for a robot to self-localize itself using a laser range finder. In addition, the self-localization becomes unstable if unexpected obstacles occlude landmarks that are important to estimate the position of the robot. There are so many factors, even the door opening and closing condition, will affect the self-localization performance. As an RFID (Radio Frequency IDentification) system uses radio waves, unlike visual sensors, it is robust against change of lighting condition or obstacles.

RFID is a wireless non-contact system that uses radio-frequency electromagnetic fields to transfer data from a tag for automatic identification and/or tracking. There are two types of communication of RFID system. One uses radio waves and the other uses electromagnetic induction for communication between reader/writer and IC tags. An RFID system based on radio wave communication using UHF[1][2][3] or SHF band realizes long distance communication[4][5][6]. However, in general, the radio wave communication based RFID system often suffers from obstacles between IC tags and antennas so that it is hard to have stable localization in an environment with many obstacles, especially, humans.

On the other hand, RFID systems based on HF[7][8][9][10][11] or LF[12] band use electromagnetic induction. The communication distance is short and less than several hundred [mm]. It is hard to estimate the distance between one antenna and a tag but it is quite accurate and reliable to detect the tag if the tag is within the range of the antenna. It rarely suffers from obstacles between IC tags and antennas. Therefore, the position estimation is more accurate than the ones based on radio wave communication with UHF or higher frequency bands.

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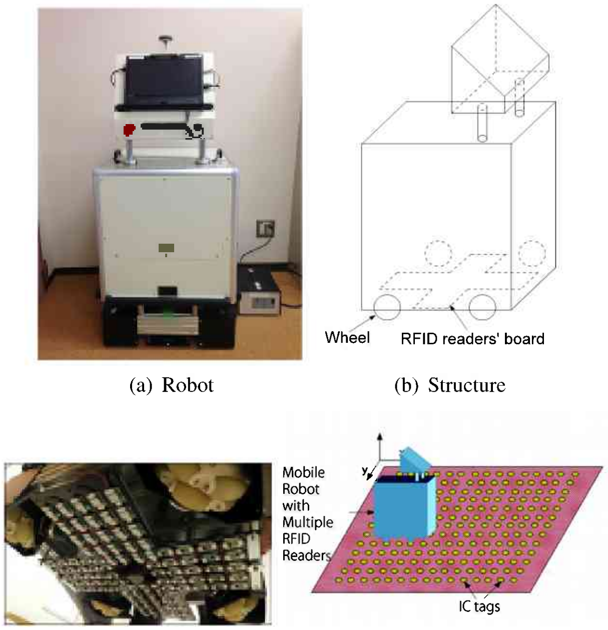
Generally, the accuracy of the RFID self-localization is easily affected by the configuration of IC tags or RFID readers. Increasing the number of RFID readers and/or the density of IC tags, in general, improves the accuracy of self-localization effectively, however, it increases production cost. It is necessary to find out an effective configuration of RFID readers and IC tags. In this paper, we build a simulator investigating the self-localization performances of different arrangements of RFID readers and IC tag textiles: two different arrangements of RFID readers and three types of IC tag textile in the simulation. The simulation results suggest that it is possible to localize the robot with less RFID readers accurately enough to navigate a robot in the environment. Experimental results also suggest that the self-localization system can quickly and accurately localize the robot itself with the proposed particle reinitializing method. Additionally, we analyze the performances of three different types of likelihood functions for a measurement model of the MCL. This paper shows three contributions as follows:

1) We analyze the performances of robot self-localization with different configurations of RFID system where the MCL based self-localization uses multiple RFID readers at the bottom of the vehicle and IC tags embedded into the floor.
2) We propose a particle reinitializing method specific to the RFID system based self-localization so that the robot localizes itself quickly and accurately.
3) We analyze three types of likelihood functions for a measurement model of the MCL based on the RFID system.

This paper is organized as follows. We give an overview of the RFID based self-localization system in Section II. The MCL based self-localization method including our simulator of the RFID system in Section III. The particle reinitializing method and three likelihood functions are also illustrated in the section. Then we introduce the configuration of the RFID readers and IC tags and all the parameters we use in the simulation. Finally, we present experimental results and illustrate how the self-localization varies along changes of the configuration of the of RFID system and different likelihood functions.



(a) Robot (b) Structure

(c) Readers (d) Robot and Environment

Fig. 1. **Self-localization** for Indoor Mobile Robot based on Multiple RFID readers and IC tags

II. SELF-LOCALIZATION BASED ON MULTIPLE RFID READERS AND IC TAGS

Figure 1 shows the indoor mobile robot self-localization system based on the multiple RFID readers and IC tags that we designed and built[11]. The 96 RFID readers are installed at the bottom of the robot as Figs.1(b) and 1(c) shows. IC tags are installed into the floor and the robot reads the tags with the RFID readers to localize itself as shown in Fig.1(d). The detailed configurations are shown in Section IV.

III. SELF-LOCALIZATION USING MCL METHOD BASED ON RFID SYSTEM

A. Monte Carlo Localization for Omni-directional Vehicle

We use a Monte Carlo Localization method, one of the probabilistic approaches[13], as Takahashi and Hashiguchi[11] use. We define the robot position and orientation in world coordinate at time t as ${}^w\boldsymbol{x}_t = ({}^wx_t, {}^wy_t, {}^w\theta_t)$. $\boldsymbol{z}_t = (r_t, tag_t)$ is measurement output at time t while tag_t is the detected tag with RFID reader r_t. A motion model ${}^w\boldsymbol{x}_{t+1} = MotionModel({}^w\boldsymbol{x}_t)$ is defined as it estimates the next robot position and orientation ${}^w\boldsymbol{x}_{t+1}$ from the current one ${}^w\boldsymbol{x}_t$. A measurement model $p(\boldsymbol{z}_t|{}^w\boldsymbol{x}_t)$ is also defined to calculate the posterior probability to receive the measurement output $\boldsymbol{z}_t$ if the robot position and orientation is ${}^w\boldsymbol{x}_t$. A set of particles is defined as a set of hypotheses of the robot position and orientation denoted at time t as $X_t = ({}^w\boldsymbol{x}_t^{[1]}, {}^w\boldsymbol{x}_t^{[2]}, \cdots, {}^w\boldsymbol{x}_t^{[M]})$, where M is the number of particles. The algorithm of the Monte Carlo Localization is shown as algorithm 1.

The motion model of the omni-directional vehicle is given

Algorithm 1 Monte-Carlo Localization

Initialize particles $X_t = ({}^w\boldsymbol{x}_t^{[1]}, {}^w\boldsymbol{x}_t^{[2]}, \cdots, {}^w\boldsymbol{x}_t^{[M]})$
for $m = 1$ to M **do**
  Update particles with the motion model: ${}^w\boldsymbol{x}_t^{[m+1]} = MotionModel({}^w\boldsymbol{x}_t^{[m]})$
  Calculate the belief of each particle with the measurement model : $w^{[m]} = p(\boldsymbol{z}_t|{}^w\boldsymbol{x}_t)$
  Update the set of particles X_t with probability $w^{[m]}$
end for
for $m = 1$ to M **do**
  draw m from X_t with probability $\propto w^{[m]}$
  add ${}^w\boldsymbol{x}_t^{[m]}$ to X_{t+1}
end for
return X_{t+1}

by Eqs.(1)(2)(3).

$$x_{t+1} = x_t + N(0, \sigma_x)\Delta t + v_x \Delta t \quad (1)$$
$$y_{t+1} = y_t + N(0, \sigma_y)\Delta t + v_y \Delta t \quad (2)$$
$$\theta_{t+1} = \theta_t + N(0, \sigma_\theta)\Delta t + \omega \Delta t \quad (3)$$

where $V = (v_x, v_y, \omega)$, Δt and $N(0, \sigma)$ indicate the velocity of the robot, period between time $t+1$ and t, Gaussian distribution with standard deviation σ, respectively.

Here we assume that tag tag_j is detected by RFID reader r_i. The position of tag tag_j detected by RFID reader antenna r_i in world coordinate ${}^w\boldsymbol{x}_{tag_j} = ({}^wx_{tag_j}, {}^wy_{tag_j}, {}^wz_{tag_j})^T$. The position of RFID reader r_i at time t in world coordinate ${}^w\boldsymbol{x}_{r_i} = ({}^wx_{r_i}, {}^wy_{r_i}, {}^wz_{r_i})^T$, which can be estimated by Eq.(4).

$$\begin{pmatrix} {}^wx_{r_i} \\ {}^wy_{r_i} \end{pmatrix} = \begin{pmatrix} \cos {}^w\theta_t & \sin {}^w\theta_t \\ -\sin {}^w\theta_t & \cos {}^w\theta_t \end{pmatrix} \begin{pmatrix} {}^rx_{r_i} \\ {}^ry_{r_i} \end{pmatrix} + \begin{pmatrix} {}^wx_t \\ {}^wy_t \end{pmatrix} \quad (4)$$

where we assume ${}^wz_{tag_j}$ and ${}^wz_{r_i}$ are constant.

Then the belief of each particle $w^{[m]}$ is calculated with the measurement model $p(\boldsymbol{z}_t|{}^w\boldsymbol{x}_t)$. $p(\boldsymbol{z}_t|{}^w\boldsymbol{x}_t)$ is one of the likelihood functions that are defined in Section III-D. In general, belief is function of the distance between the detected tag and the reader that detects it.

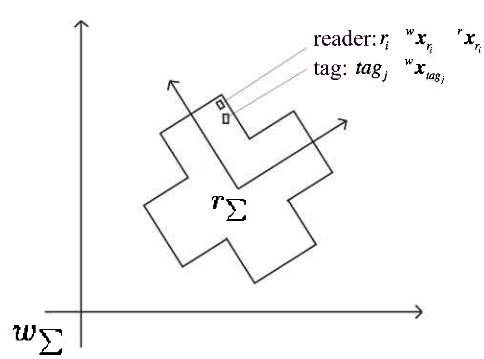


Fig. 2. World coordinate system ${}^w\Sigma$ and robot coordinate system ${}^r\Sigma$

After the beliefs of particles $w^{[m]}$ are calculated, it estimates the position of the robot as weighted mean of the particles.

$$\boldsymbol{x}_t = \frac{\sum_{m=1}^{M} w^{[m]} \boldsymbol{x}_t^{[m]}}{\sum_{m=1}^{M} w^{[m]}} \tag{5}$$

Then the set of the particles is updated from X_t to X_{t+1} with probability proportional to the belief $w^{[m]}$.

B. Reinitializing of particles

Particles ${}^w\boldsymbol{x}_t = ({}^w x_t, {}^w y_t, {}^w \theta_t)$ are resampled by Eq.(6) :

$$\begin{pmatrix} {}^w x_t \\ {}^w y_t \end{pmatrix} = \begin{pmatrix} {}^w x_{tag_j} \\ {}^w y_{tag_j} \end{pmatrix} - \begin{pmatrix} \cos {}^w\theta_t & -\sin {}^w\theta_t \\ \sin {}^w\theta_t & \cos {}^w\theta_t \end{pmatrix} \begin{pmatrix} {}^r x_{r_i} \\ {}^r y_{r_i} \end{pmatrix} \tag{6}$$

where ${}^w\theta_t$ is generated with uniform random function from $-\pi$ to π. The reinitializing indicates that the robot on the position where the RFID reader r_i is just above the detected tag tag_j, and the position of the robot $({}^w x_t, {}^w y_t)$ is distributed over the orientation ${}^w\theta_t$ under the constraint. The proposed reinitializing leads the self-localization system to localize the robot itself quickly and stably because it can eliminate unnecessary particles distributed over the possible exploration space.

C. RFID tag detection model

Actually, a HF-band RFID reader detects a tag reliably if the tag is in the detection range. We model the detection range as follows.

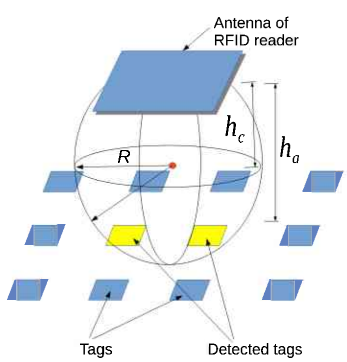


Fig. 3. Definition of Tag Detection Range for Simulation

Figure 3 shows the area where one reader detects the tag. The sphere drawn with solid black line stands for the detection range of one RFID reader. The radius of detection range is R. The red point represents the center of the detection range which is just below the RFID reader antenna with the distance of h_c. The hight of one RFID reader antenna is h_a. A tag is detected if and only if the tag is within the detection range of one RFID reader antenna. Eq.(7) shows the condition of the tag detection.

$$({}^w\boldsymbol{x}_{r_i} - {}^w\boldsymbol{x}_{tag_j})^2 + ({}^w\boldsymbol{y}_{r_i} - {}^w\boldsymbol{y}_{tag_j})^2 + (h_a - h_c - {}^w\boldsymbol{z}_{tag_j})^2 < R^2 \tag{7}$$

D. Likelihood functions

Figure 4 shows three types of likelihood function model. Model 1 uses a Gaussian distribution function $N(0, \sigma)$ to calculate the likelihood of a particle. Model 2 uses the digital type, the beliefs of particles only have two values, 0 and 1; The likelihood is 1 if the tag is within the range of σ, else 0, otherwise. Model 3 is defined by the combination of Model 1 and 2, as Eq.(8) shows.

$$p(tag_j, r_i) = \begin{cases} 1 \text{ if } \mu - \sigma/2 < d < \mu + \sigma/2 \\ \beta \exp\left(-\frac{1}{2\sigma^2} d^2\right) \text{ else} \end{cases} \tag{8}$$

where $d = \sqrt{({}^w\boldsymbol{x}_{tag_j} - {}^w\boldsymbol{x}_{r_i})^2}$ and β is a constant.

Model 1, as Fig.4(a) shows, the particles tend to gather around μ with beliefs calculated by Gaussian distribution function, because the more closer, the higher probability is. Model 2, all particles are distributed in the range of σ and particles are not going to gather around. The belief is 1 if a particle is within the range of σ, or 0 if it is out of the range of σ. Model 3, within the range of $\sigma/2$, particles are distributed as likelihood function 2. The difference is that there are also particles gathering around out the range of $\sigma/2$. As mentioned before, the position of the robot is estimated by Eq.(5) by the weighted mean of the particles. We try to figure out which model is more suitable for the system.

IV. SIMULATIONS AND ANALYSIS

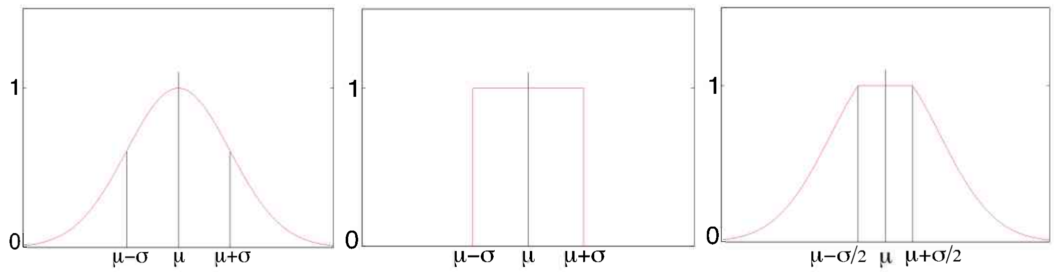
Figure 5(a) shows the arrangement of the 96 RFID readers. Antennas are divided into four parts and the intervals of every two antennas are l_1 = 44.5 and l_2 = 37.5 [mm]. The antenna size of one reader is by 30×30 [mm]. The height of the antenna h_a is set to 20 [mm]. The detecting radius R = 15 [mm]. The center of the detecting region of a reader antenna is just below the antenna with h_c = 8 [mm].

Figure 5(b) shows another arrangement of the RFID readers. We reduce 96 RFID readers to 24 RFID readers to cut down the cost of the system. $l_1 \times l_2$ are set as 70×90 [mm]. The antenna size of one reader is 60×60 [mm]. R, h_a, and h_c shown in Fig.3 are 30 [mm], 45 [mm], and 24 [mm], respectively.

The size of an IC tag is 10×20 [mm]. The IC tags are uniformly distributed in a square pattern with various densities of IC tags, $100 tags/m^2$, $25 tags/m^2$, $16 tags/m^2$. The interval of every two tags of the 3 ideal textiles are 100, 200, 250 [mm], respectively.

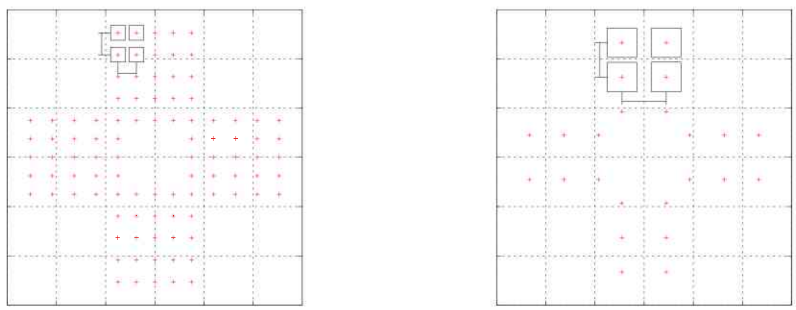
Figure 6 shows the ground truth of the robot trajectories. The robot runs following these paths with different orientations, 0, $\pi/6$, and $\pi/4$ [rad]. As Fig.6(a) shows, the interval of every two paths is presented by d, where d is 1/5 of the interval of every two tags.

Tables I to IV show the mean, maximum and variance of localization errors according to different configurations. We ignore the initial data of the localization to calculate the data of the tables in order to eliminate the poor estimation result at the initial situation. The proposed particle reinitializing method enables to localize the robot quickly and reach a stable estimation state. From the simulation results, we easily



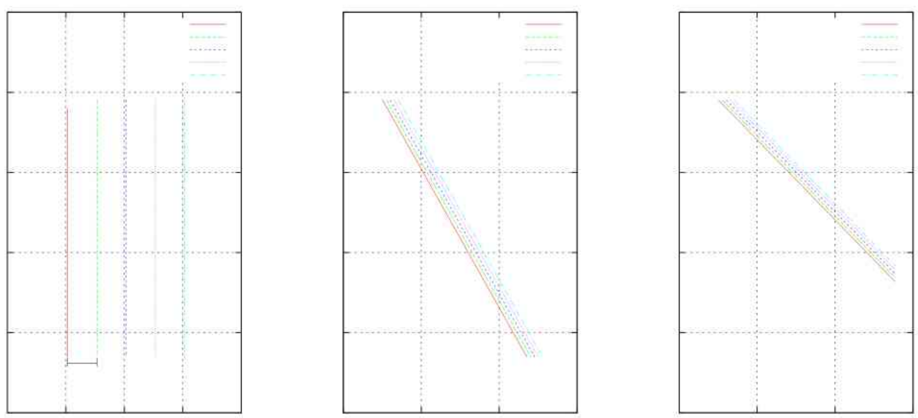
(a) Model 1 (b) Model 2 (c) Model 3

Fig. 4. Likelihood functions for Measurement Model



(a) 96 RFID reader antennas (b) 24 RFID reader antennas

Fig. 5. Arrangements of RFID readers



(a) 0 (b) $\pi/6$ (c) $\pi/4$

Fig. 6. Ground truth with different orientation

figure out that the performance of the one with the density of $100tags/m^2$ is the best no matter which configuration of RFID system we use among the three different types of IC tag textiles. This result suggests that if the IC tag density is $100tags/m^2$, we can use much less number of RFID readers within a certain range of estimation error.

A. Experimental results with the configuration of 96 RFID reader antennas

First, Model 1 is tested as the likelihood function as Table I shows the statistical data. In condition of IC tag textile $100tags/m^2$, Table I illustrates that position estimation error is quite small under the configuration of 96 RFID readers. It localizes itself very precisely even in the beginning stage The average position errors of five paths are less 5 [mm] for both x and y axises, and the orientation error is less than 0.01 [rad]. Even max errors are less than 10[mm] and the orientation error is less than 0.05[rad]. The system is very stable as variances are less than 3 [mm].

For conditions of IC textiles $25tags/m^2$ and $16tags/m^2$, the experimental results are also good, but as the variances in Table I show self-localization with IC tag textile of $100tags/m^2$ is the most stable. The variances of IC textiles $25tags/m^2$ and $16tags/m^2$ are much bigger than the ones of IC tag textile $100tags/m^2$, especially in case of IC tag textile $16tags/m^2$.

Table I shows that the experimental results of textile $25tags/m^2$ are better than ones of textile $16tags/m^2$ in the conditions of orientation $\pi/6$ and $\pi/4$. But in condition of orientation 0, the simulation result of IC tag textile $16tags/m^2$ is better than the one of textile $25tags/m^2$. This is because the IC tags and the RFID readers are both arranged in a square pattern. On one side, sometimes, the system can not detect any tags, particularly, when the robot moves forward along x or y direction. On the other side, the detecting range of one reader with this configuration is very narrow and small. Most importantly, we can not ensure that the paths we choose is suitable for all textiles we use. Those factors lead to the result that the self-localization with $16tags/m^2$ textile is better than the one with $25tags/m^2$ textile betweentimes. The difference between $16tags/m^2$ textile and $25tags/m^2$ textile is not as much as $25tags/m^2$ textile and $100tags/m^2$ textile.

B. Experimental results with the configuration of 24 RFID reader antennas

1) Configuration with likelihood function: Model 1: The experimental results is shown in Table II. Compared with the experimental results of 96 RFID readers, the estimated position errors are little bigger than the ones of 96 RFID readers for all the three types of IC tag textiles. But the self-localization results are still good enough for robot self-localization with configuration of 24 RFID readers while the number of readers reduced to 1/4 of the 96 RFID readers.

In condition of textile $100tags/m^2$, the average position errors are still less than 10[mm] and max errors are less than 20[mm]. There is no doubt that the performance with $100tags/m^2$ textile is better than the performances of the other two textiles. The difference is that under the configuration of 24 RFID readers with likelihood function model 1, the performances of IC tag textile $16tags/m^2$ are better than the ones of textile $25tags/m^2$. Actually, the performance of $25tags/m^2$ should be better than the one of $16tags/m^2$. Besides the factors we described in the configuration os 96 RFID reader antennas, there is also another reason lead to this result. As we mentioned previously, we can not ensure that the paths we choose is suitable for all textiles we use. Here, we reduce the number of RFID readers, which aggravates that the system detect less RFID readers in the paths under the condition of $25tags/m^2$ textile than the situation of $16tags/m2$ textile. Table III and Table IV prove that. When we change the likelihood function model, the performance of $25tags/m^2$ are better than the one of $16tags/m^2$.

2) Configuration with likelihood function: Model 2: The simulation results are shown in Table III. Nearly the same as the configuration of 96 RFID readers, the localization errors are less than 10 [mm] in x and y axes with three different types of tag textiles. The performances in case of IC tag textile $100tags/m^2$ is the best. The one of textile $25tags/m^2$ is better than the performance of textile $16tags/m^2$. Compared with the results of the configuration with likelihood Model 1, the performance of the one with likelihood Model 2 is much better.

3) Configuration with likelihood function: Model 3: Table III shows the experimental results of the configuration with likelihood Model 3. The performances of the configuration with likelihood Model 3 is not better than the ones of configurations with likelihood Model 1 and 2. But the performance of the configuration with likelihood Model 3 is also good enough for mobile robot self-localization.

From the simulation results, we find that all the configurations we use in the simulation can localize the robot itself well. The average position errors are less than 20 [mm], which are good enough for a robot self-localization. Among the different configurations of RFID system, the performance of the configuration with 96 RFID readers is good, however, the cost is high, relatively. For the three different types of IC tag textiles, the performance of the one with the density of $100tags/m^2$ is the best. The variances shown in Tables III and IV illustrate that the RFID system is much stable with the configuration of $25tags/m2$ textile than the configuration of $16tags/m^2$ textile.

It is very necessary to figure out efficient configuration to develop a low cost RFID system. We enlarged the RFID antennas and developed a new RFID system with 24 RFID readers. The simulations show it localizes a robot well. In the simulations of configuration with 24 RFID readers, we apply three types of likelihood functions, Model 1, 2, and 3. The experimental results illustrate that the performance of likelihood function Model 2 is better than the other two.

V. CONCLUSIONS

In this paper, we first developed a computational simulation based on RFID system using MCL method, and analyzed the performances of different configurations of RFID system including different arrangements of RFID readers and different types of IC textiles. Then, we improved the self-localization with the proposed particle reinitializing method. The proposed particle reinitializing method enables the system to reach the stable localization state quickly and it also makes the self-localization more accurate and stable. Additionally, we applied three types of likelihood functions to the RFID system to optimize the self-localization. Finally, we presented the experimental results illustrating how the self-localization accuracy varies along changes of the different configurations of RFID system. The experimental results illustrate that with the configuration of 24 RFID readers the system can also self-localize well. The results show that the self-localization based on MCL works accurately enough for realistic situation even using 24 RFID readers on the vehicle and lower density IC tag textiles on the floor, which could greatly reduce the cost compared with 96 RFID readers.

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TABLE I

PERFORMANCES OF SELF-LOCALIZATION WITH THE CONFIGURATION OF 96 RFID READER ANTENNAS

96 RFID reader antennas	likelihood	orientation [rad]	error by Mean			error by Max			variance		
			x [mm]	y [mm]	θ [rad]	x [mm]	y [mm]	θ [rad]	x [mm]	y [mm]	θ [rad]
		0	1.9	1.4	0.007	6.0	5.5	0.022	1.4	1.2	0.000
$100tags/m^2$	Model 1	$\pi/6$	2.4	1.9	0.008	8.8	7.6	0.029	2.5	1.6	0.000
		$\pi/4$	3.4	3.3	0.008	9.2	9.0	0.025	2.7	2.6	0.000
		0	7.3	10.2	0.047	43.4	26.3	0.078	37.7	30.6	0.000
$25tags/m^2$	Model 1	$\pi/6$	4.5	4.4	0.021	19.3	13.3	0.048	12.8	9.7	0.000
		$\pi/4$	4.0	4.3	0.018	14.1	12.7	0.045	6.6	6.5	0.000
		0	4.8	1.9	0.019	11.4	6.3	0.044	4.7	2.0	0.000
$16tags/m^2$	Model 1	$\pi/6$	6.9	7.5	0.068	36.9	66.6	0.648	58.1	429.6	0.081
		$\pi/4$	4.1	4.2	0.022	15.0	21.3	0.147	14.3	89.2	0.016

TABLE II

PERFORMANCES OF SELF-LOCALIZATION WITH THE CONFIGURATION OF 24 RFID READER ANTENNAS

24 RFID reader antennas	likelihood	orientation [rad]	error by Mean			error by Max			variance		
			x [mm]	y [mm]	θ [rad]	x [mm]	y [mm]	θ [rad]	x [mm]	y [mm]	θ [rad]
		0	3.9	3.3	0.016	9.5	7.1	0.038	3.7	2.2	0.000
$100tags/m^2$	Model 1	$\pi/6$	3.3	2.5	0.016	12.0	9.4	0.048	4.7	2.8	0.000
		$\pi/4$	7.5	4.8	0.026	14.6	11.7	0.052	4.6	4.3	0.000
		0	9.9	2.9	0.014	15.8	9.4	0.030	3.9	3.7	0.000
$25tags/m^2$	Model 1	$\pi/6$	8.5	5.2	0.024	26.1	14.1	0.061	30.0	8.8	0.000
		$\pi/4$	12.7	10.1	0.046	28.3	30.4	0.079	32.2	56.4	0.000
		0	9.5	4.6	0.020	14.1	10.5	0.029	3.0	3.1	0.000
$16tags/m^2$	Model 1	$\pi/6$	6.9	4.6	0.021	21.6	13.9	0.055	18.1	8.1	0.000
		$\pi/4$	8.1	7.9	0.010	17.5	15.4	0.030	7.9	6.5	0.000

TABLE III

PERFORMANCES OF SELF-LOCALIZATION WITH THE CONFIGURATION OF 24 RFID READER ANTENNAS

24 RFID reader antennas	likelihood	orientation [rad]	error by Mean			error by Max			variance		
			x [mm]	y [mm]	θ [rad]	x [mm]	y [mm]	θ [rad]	x [mm]	y [mm]	θ [rad]
		0	2.8	2.7	0.008	8.6	8.0	0.022	2.8	2.4	0.000
$100tags/m^2$	Model 2	$\pi/6$	2.7	2.3	0.009	11.7	9.0	0.028	3.6	2.4	0.000
		$\pi/4$	6.4	5.9	0.010	14.5	12.9	0.027	4.2	4.6	0.000
		0	9.5	4.6	0.020	14.1	10.5	0.029	3.0	3.1	0.000
$25tags/m^2$	Model 2	$\pi/6$	6.9	4.6	0.021	21.6	13.9	0.055	18.1	8.1	0.000
		$\pi/4$	8.1	7.9	0.010	17.5	15.4	0.030	7.9	6.5	0.000
		0	9.6	4.3	0.014	15.5	11.4	0.027	5.6	5.5	0.000
$16tags/m^2$	Model 2	$\pi/6$	8.3	6.2	0.014	23.9	16.8	0.041	22.7	12.7	0.000
		$\pi/4$	7.8	7.7	0.018	20.0	16.5	0.040	13.9	10.7	0.000

TABLE IV

PERFORMANCES OF SELF-LOCALIZATION WITH THE CONFIGURATION OF 24 RFID READER ANTENNAS

24 RFID reader antennas	likelihood	orientation [rad]	error by Mean			error by Max			variance		
			x [mm]	y [mm]	θ [rad]	x [mm]	y [mm]	θ [rad]	x [mm]	y [mm]	θ [rad]
		0	4.4	4.9	0.035	9.6	12.0	0.046	4.4	9.5	0.000
$100tags/m^2$	Model 3	$\pi/6$	5.2	4.2	0.044	16.3	16.3	0.066	10.7	8.8	0.000
		$\pi/4$	9.7	9.0	0.013	21.6	21.3	0.026	19.0	19.5	0.000
		0	12.4	5.0	0.026	22.3	11.2	0.048	16.1	7.7	0.000
$25tags/m^2$	Model 3	$\pi/6$	7.8	5.7	0.034	25.1	17.4	0.073	23.6	13.6	0.000
		$\pi/4$	8.4	7.9	0.016	19.6	17.5	0.041	12.5	11.3	0.000
		0	10.6	5.0	0.016	25.9	18.4	0.044	19.7	13.4	0.000
$16tags/m^2$	Model 3	$\pi/6$	9.5	9.1	0.050	41.2	30.0	0.122	56.9	44.1	0.000
		$\pi/4$	10.0	9.6	0.039	28.7	27.2	0.086	26.6	34.7	0.000

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