Particle Filter based Landmark Mapping for SLAM of Mobile Robot based on RFID System

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Abstract— **This paper proposes a novel Simultaneous Localization and Mapping (SLAM) based on distributed particle updates for landmark mapping and validates it with an HF-band RFID-based mobile robot. Multiple RFID readers are embedded at the bottom of an omni-directional vehicle and tags are installed on the floor. The IC tags are used as landmarks of the environment. FastSLAM[1] uses particles to estimate the position and orientation of the robot and Kalman filter to update the positions of IC tags. However, an update of the detected IC tags with Kalman filter is not appropriate because the probability of the IC tag detection cannot be modeled with a Gaussian distribution. We use two separate particle filters to estimate both the position and orientation of the robot and positions of IC tags simultaneously. The proposed method has been tested on the simulated and real environments. Experimental results show the validity and computational efficiency of the proposed method.**

I. INTRODUCTION

Simultaneous localization and mapping, as known as SLAM, is a technique for performing self-localization and map building simultaneously. FastSLAM is one of the popular landmark-based SLAM algorithms[2].FastSLAM adopts a particle filter to estimate the robot pose and positions of a fixed number of predetermined landmarks and tracks the position of the landmark using an extended Kalman filter (EKF)[3].

RFID (Radio Frequency IDentification) system as an automatic identification device for a mobile robot has been studied[4].Since RFID system uses an electric wave, unlike the visual sensor used for conventional mobile robots, it is robust against the influence of obstacles outside of RFID communication area or lighting conditions. Therefore, it is useful for landmark-based SLAM for a mobile robot.

Wang and Takahashi[5] use the FastSLAM method to localize a robot and build a map of IC tags simultaneously in an unknown environment. The RFID system can be used as a good landmark detector with small measuring error so that the error is about 25[mm]. However, a large number of RFID readers are needed to cover a wide range to detect the IC tags on the floor. As we designed 96 RFID readers on the bottom of the vehicle, they are so expensive and consume a lot of electric power. Mi and Takahashi[6] have proposed a RFID configuration with 8 readers for the self-localization of a mobile robot and showed the proposed system performs with small localization error and it is less expensive than the one of 96 readers. However, Kalman filter is not fit to estimate the positions of IC tags because the tag detection area cannot be modeled with a Gaussian distribution. Therefore, we propose to use particle filter to mapping IC tag.

Deyle et al.[7] presents a particle filter implementation for estimating the pose of UHF RFID tags in the environment with respect to an RFID-equipped robot. As they focus on estimating the pose of UHF RFID tags, the estimation of position and orientation of the robot is based on the odometry. The idea of using particle filter to estimate the positions of tags gives us great enlightenment for our simultaneous localization and mapping.

Eliazar and Parr[8] have tried a method of simultaneous localization and mapping both by particle-filter-based on a laser penetration model. In their research, each particle corresponds to a distinct hypothesis about the map and the robot position and orientation within the map. Their algorithm is based purely on laser system and it is not for a landmark-based SLAM.

This paper focuses on utilizing particle filters for both the robot localization and building a map of landmarks independently. Each detected IC tag is regarded as a landmark and updated by one particle set. Localization of the robot is also estimated by one particle set. All particle filters work independently so that the proposed method keep computational resources and calculation cost as small as possible. This paper also introduces the difference between the proposed method with Kalman-filter-based FastSLAM and compare these two methods in the same experimental condition. Experimental results show the validity and computational efficiency of the proposed method.

II. RFID SYSTEM IN THIS RESEARCH

RFID system uses radio-frequency electromagnetic fields to transfer data from a tag attached to an object for automatic object identification and/or tracking. Each tag has a unique ID that can be utilized as a landmark ID.

HF-band RFID system[9] use electromagnetic induction. In general, the communication distance is shorter and speed is lower than radio waves methods [10], but the communication is robust against obstacles around the antennas or tags and environmental changes. It is a good property for robot self-localization because it can detect the tags reliably and the position can be specified precisely.

Figure 1 shows the indoor mobile robot with the multiple RFID readers and an IC tags textile carpet that we designed and built.RFID readers are installed on the bottom of the robot as Figs.1(b) and 1(c) shows. IC tags are installed on the floor. Fig.1(d) shows one of the floor carpets that IC tags are installed in. The robot reads the tags with the RFID

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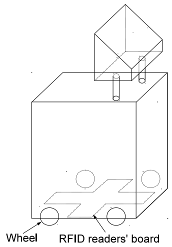
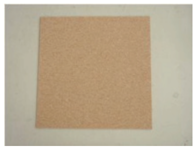
(a) Robot



(b) Drawing

(c) Readers



(d) IC tag Textile Carpet

Fig. 1. Indoor Mobile Robot Embedding Multiple RFID Readers and IC Tags Textile Carpet

readers to localize itself by reading the IC tags installed on the floor. Each IC tag has its own ID. The distribution of these IC tags is unknown when they are installed on the floor. These IC tags will be used as landmarks to execute the SLAM work.

III. SLAM ON HF-BAND RFID SYSTEM

The conditional independence property of the SLAM problem implies that the posterior Equation (1) can be factored as follows:

$$\begin{aligned} & p({}^{w}\boldsymbol{x}_r(t), {}^{w}\boldsymbol{x}_{tag_{1:N}} \mid \boldsymbol{z}(t), \boldsymbol{u}(t), n(t)) \\ & = p({}^{w}\boldsymbol{x}_r(t) \mid \boldsymbol{z}(t), \boldsymbol{u}(t), n(t)) \\ & p({}^{w}\boldsymbol{x}_{tag_{1:N}} \mid{}^{w} \boldsymbol{x}_r(t), \boldsymbol{z}(t), \boldsymbol{u}(t), n(t)) \end{aligned} \tag{1}$$

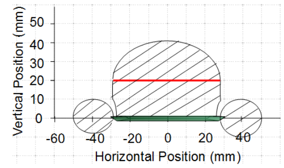
where ${}^{w}\boldsymbol{x}_r(t) = ({}^{w}x_r, {}^{w}y_r, {}^{w}\theta_r)$ is position and posture of the robot in world coordinate system at time t, ${}^{w}\boldsymbol{x}_{tag_{1:N}}$ is positions of tags in world coordinate, $\boldsymbol{z}(t)$ is observation at time t, $\boldsymbol{u}(t)$ is robot control at time t, and $n(t)$ is index of the landmark detected at time t.

A. FastSLAM on HF-band RFID System

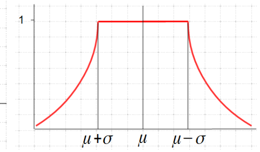
We briefly review FastSLAM here. FastSLAM is mainly based on a particle filter. One particle $[m]$ consists of information of the robot pose ${}^{w}\boldsymbol{x}_r^{[m]}(t)$ and the locations of tags ${}^{w}\boldsymbol{x}_{tag_{1:N}}^{[m]}$ in the world coordinate system where N is the number of the tags. The location of the tag n is represented by a Gaussian distribution. $\mu_n^{[m]}(t)$ and $\Sigma_n^{[m]}(t)$ are the center vector and the covariance matrix of the Gaussian distribution. FastSLAM exploits the factored representation by maintaining the $N+1$ filters. Each FastSLAM particle is of the form:

$$\begin{aligned} & {}^{w}\boldsymbol{x}^{[m]}(t) = <{}^{w} \boldsymbol{x}_r^{[m]}(t), \omega_n^{[m]}, \mu_1^{[m]}(t), \Sigma_1^{[m]}(t), \ldots, \mu_N^{[m]}(t), \\ & \Sigma_N^{[m]}(t) > \end{aligned} \tag{2}$$

where ω_n^m is the importance weight of particle $[m]$. ω_n^m is calculated with a measurement model. The measurement model is a likelihood function $p(\boldsymbol{z}(t) \mid{}^{w} \boldsymbol{x}_r(t))$. A Gaussian distribution is commonly used for the likelihood function.



(a) detection range of RFID reader with large antenna (the green part is the reader)



(b) likelihood model of tag detection at the 20 [mm] height

Fig. 2. The detection range of RFID reader using large antenna and likelihood model of tag detection

The new particle set incorporates the control input $\boldsymbol{u}_t$ with a robot motion model and measurement information $\boldsymbol{z}_t$ to update the robot pose ${}^{w}\boldsymbol{x}^{[m]}(t)$ and the important weight ω_n^m accordingly. The filtering is based on the important weight ω_n^m. The parameters of tag location $\mu_n^{[m]}(t)$ and $\Sigma_n^{[m]}(t)$, are updated using EKF. Each EKF tracks a single tag position and it assumes a Gaussian distribution for the measurement of the tag. In total, there are $N \cdot M$ EKFs where M is the total number of particles in the particle filter.

B. SLAM based on Independent Particle Filters for Landmark Mapping and Localization for HF-band RFID System

We propose a new SLAM method that utilizes independent particle filters for landmark mapping and localization. Using particles to estimate both poses of the robot and IC tags' positions, we make $N+1$ particle sets each of which is assigned by one particle filter. One robot particle set is for estimating the position and orientation of the robot. Each robot particle is of the form:

$$\boldsymbol{x}_r^{[m]}(t) = <{}^{w} \boldsymbol{x}_r^{[m]}(t), \omega_r^{[m]}(t) > \tag{3}$$

N tag particle sets are for estimating the positions of N detected tags. Each tag particle is of the form:

$$\boldsymbol{x}_n^{[l]} = <{}^{w} \boldsymbol{x}_n^{[l]}, \omega_n^{[l]} > \tag{4}$$

where ${}^{w}\boldsymbol{x}_n^{[l]} = ({}^{w}x_n, {}^{w}y_n)$ is the position of tag n in world coordinate system represented by particle l and $\omega_n^{[l]}$ is the importance weight of the tag particle. The calculation of importance weight of both robot particle and tag particle are based on the tag detection model.

Fig.2(a) shows the tag detection model of RFID reader with the large antenna. We choose the height of 20[mm] to ensure the large range of tag detection and protect the reader as well. At the height of 20[mm], the likelihood distribution of tag detection can be modeled as Fig.2(b). The likelihood function is defined as:

$$\omega = \begin{cases} 1, & if\ e < \sigma \\ \beta \exp\left(-\frac{1}{2\sigma^2} e^2\right), & else \end{cases} \tag{5}$$

σ = 30[mm] when the reader at the height of 20 [mm]. $e = \sqrt{({}^{w}\boldsymbol{x}_n - {}^{w}\boldsymbol{x}_i)^2}$. β is a constant to regulate the ω so that

$\omega = 1$ when $e = \sigma$ (β=1.618 for σ = 30[mm]). ${}^w\boldsymbol{x}_i$ is the position of the RFID reader i which detected tag n in the world coordinate system. ${}^w\boldsymbol{x}_i = ({}^w x_i, {}^w y_i)^{\mathrm{T}}$ can be calculated by Eq.6.

$$\begin{pmatrix} {}^w x_i \\ {}^w y_i \end{pmatrix} = \begin{pmatrix} {}^w x_r \\ {}^w y_r \end{pmatrix} + \begin{pmatrix} \cos^w \theta_r & -\sin^w \theta_r \\ \sin^w \theta_r & \cos^w \theta_r \end{pmatrix} \begin{pmatrix} {}^r x_i \\ {}^r y_i \end{pmatrix} \quad (6)$$

where $({}^r x_i, {}^r y_i)$ is position of the RFID reader i in the robot coordinate system.

Algorithm 1 SLAM based on Independent Particle Filters for Landmark Mapping and Localization:

1: $\boldsymbol{S}_r(t) = (\boldsymbol{x}_r^{[1]}(t), \boldsymbol{x}_r^{[2]}(t), \cdots, \boldsymbol{x}_r^{[M]}(t))$, $\boldsymbol{S}_n$
2: **for** $m = 1$ to M **do**
3:   Update particles with the motion model: ${}^w\boldsymbol{x}_r^{[m]}(t) = MotionModel({}^w\boldsymbol{x}_r^{[m]}(t-1))$
4: **end for**
5: **if** tag n is detected **then**
6:   **if** tag n is never seen before **then**
7:     Initialize tag particles $\boldsymbol{S}_n = (\boldsymbol{x}_n^{[1]}, \boldsymbol{x}_n^{[2]}, \cdots, \boldsymbol{x}_n^{[L]})$
8:   **else**
9:     **for** $l = 1$ to L **do**
10:       update $\omega_n^{[l]}$ based on the measurement model
11:     **end for**
12:   **end if**
13:   ${}^w\boldsymbol{x}_n(t) = \frac{\Sigma_{l=1}^{L} {}^w\boldsymbol{x}_n^{[l]}(t)\omega_n^{[l]}(t)}{\Sigma_{l=1}^{L}\omega_n^{[l]}(t)}$
14:   **for** $l = 1$ to L **do**
15:     **if** $(\omega_n^{[l]}(t) \leq threshold_{tag})$ **then**
16:       reset ${}^w\boldsymbol{x}_n^{[l]}$ with the one of another tag particle with large importance weight
17:     **end if**
18:   **end for**
19:   **for** $m = 1$ to M **do**
20:     update $\omega_r^{[m]}$ based on the measurement model
21:   **end for**
22: **end if**
23: ${}^w\boldsymbol{x}_r(t) = \frac{\Sigma_{m=1}^{M} {}^w\boldsymbol{x}_r^{[m]}(t)\omega_r^{[m]}(t)}{\Sigma_{m=1}^{M}\omega_r^{[m]}(t)}$
24: **for** $m = 1$ to M **do**
25:   **if** $(\omega_r^{[m]}(t) \leq threshold_r)$ **then**
26:     reset ${}^w\boldsymbol{x}_r^{[m]}$ with the one of another robot particle with large importance weight
27:   **end if**
28: **end for**
29: return $\boldsymbol{S}_r(t)$, $\boldsymbol{S}_n$

Algorithm 1 shows the algorithm of our proposed SLAM based on independent particle filters for landmark mapping and localization. First, it updates the particles of the position and orientation of the robot by the motion model. The motion model is given by Eq.(7).

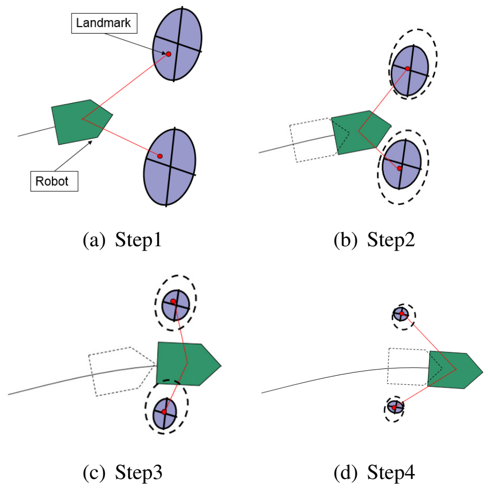
$$\begin{aligned} {}^w x_r(t) &= {}^w x_r(t-1) + v_x\Delta t + \varepsilon_x\Delta t, \quad \varepsilon_x \sim N(0,\sigma_x) \\ {}^w y_r(t) &= {}^w y_r(t-1) + v_y\Delta t + \varepsilon_y\Delta t, \quad \varepsilon_y \sim N(0,\sigma_y) \\ {}^w \theta_r(t) &= {}^w \theta_r(t-1) + \omega\Delta t + \varepsilon_\theta\Delta t, \quad \varepsilon_\theta \sim N(0,\sigma_\theta) \end{aligned} \quad (7)$$

where $V = (v_x, v_y, \omega)$ and Δt indicate the velocity of the robot and period between time $t-1$ to t, respectively. $N(0,\sigma)$ means the Gaussian distribution with standard deviation σ. During the movement, if the robot detected one tag, the robot should judge this tag whether it is the first time detected by the ID of this tag. If it is the first detection of the tag, one particle set is initialized with a certain importance weight and these particles are distributed around the reader which detected this tag. Otherwise, the likelihood function Eq.(5) is used to calculate the importance weight for each particle as shown in line 10 of **Algorithm 1**. Then, the position of this detected tag is calculated based on the importance weight of each tag particles. At the resampling step of particle representing the tag position, the particle with small importance weight will change to the state of one of the particles with large importance weight. After the update of the detected tag, the position and orientation of the robot are estimated based on the estimation of the detected tag. To estimate the pose of the robot, the importance weight of each robot particle will be updated by the likelihood function Eq.(5), again. The estimated position of the detected tag is used as the observation data at line 20 in **Algorithm 1**. The updated importance weights of these robot particles are used for the estimation of the pose of the robot. At last, the poses of the robot particles with small importance weight are assigned to the poses of one of the particles with large importance weight. It repeats this procedure.

C. Comparison between FastSLAM and SLAM with Independent Particle Filters for Landmark Updating and Localization

Figure.3 illustrates the estimation of landmarks in FastSLAM. If the robot detects a new landmark for the first time, this landmark requires an initialization of a new Kalman filter based on the estimated pose of the robot. As shown in Fig.3(a), the uncertainty of landmarks is very large. By detecting the IC tag multiple times, Kalman filter recursively updates to converge constantly the optimal position of the detected IC tag. The uncertainty of positions of IC tags in Fig.3(d) is much smaller than Fig.3(a). The convergence of the estimated IC tag position is based on the assumption that the tag detection follows a Gaussian distribution. As we discussed in the last section, the tag detection of the HF-band RFID system does not follow a Gaussian distribution as shown in Fig.2. If the assumption is not guaranteed, the estimated IC tag position does not converge.

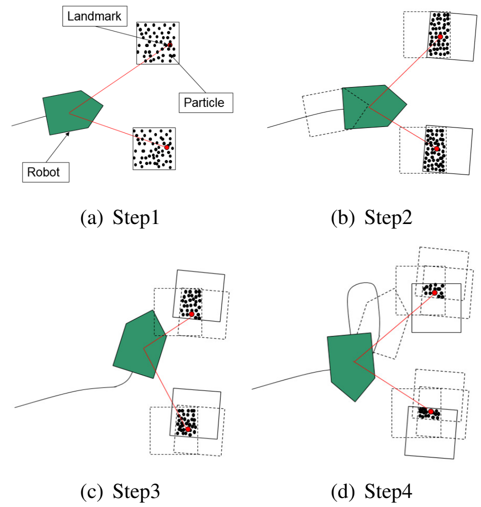
Figure 4 illustrates the estimation of landmarks by SLAM with particle-filter-based landmark updating. As shown in Fig.4(a), if the robot detects a new landmark for the first time, the particles are distributed randomly in the tag detection area of the antenna. When the robot detects this IC tag in another location, another detection area is defined as shown in Fig.4(b). Integrating this detection area with the last detection area in step 1, the smaller possible area of the detected IC tag can be defined. So if the robot can detect IC tags at more different locations to make the possible area smaller, it will get more accurate positions of detected IC



(a) Step1 (b) Step2

(c) Step3 (d) Step4

Fig. 3. Estimation of landmarks in FastSLAM:ellipse means the uncertainty of the position of IC tag



(a) Step1 (b) Step2

(c) Step3 (d) Step4

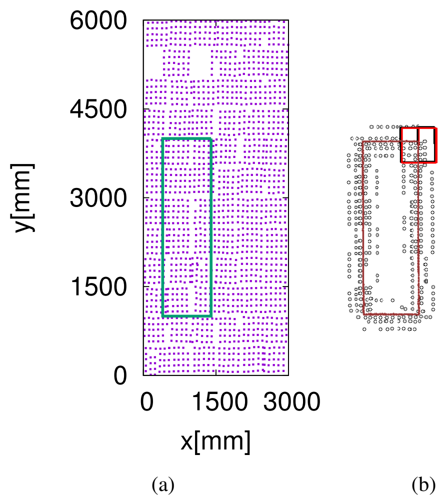
Fig. 4. Estimation of landmarks by SLAM with particle-filter-based landmark updating (rectangle means the possible area of detected IC tag)

tags as shown in Fig.4(d).

SLAM with independent particle filters for landmark updating and localization is applicable not only to the case in which landmark sensing can be modeled with a Gaussian distribution but also to the case in which landmark detection can not be modeled with a Gaussian distribution. The particle in FastSLAM is defined as Eq.(2). The particle in the SLAM with independent particle filters for landmark updating and localization are defined as Eq.(3) and Eq.(4). Without using the balanced binary tree, FastSLAM requires memory size $O(MN)$, our proposed method requires $O(M+LN)$. We set $M=1000$ robot particles to estimate the position and orientation of the robot both in FastSLAM and the proposed method. The proposed method uses $L=150$ particles for the estimation of one detected tag position. With the increase of detected IC tags, when $N \geq 2$, $O(MN) \geq O(M+LN)$. From the point of view of calculation cost, when the robot detects one IC tag, FastSLAM has $(3+1+2+3)*M$ parameters (3 robot position parameters, 1 importance weight, 2 parameters of $\mu_1^{[m]}(t)$ and 3 parameters of $\Sigma_1^{[m]}(t)$ in each particle) to be updated. The proposed method needs $(3+1)*M+(2+1)*L$ parameters (3 position parameters and 1 importance weight in each robot particle and 2 position parameters and importance weight in each tag particle) to be updated. So FastSLAM has 9000 parameters need to be updated, on the other hand, the proposed method just needs 4450 parameters to update. This makes the proposed method faster than FastSLAM especially when the particles for estimating the position of the robot increase.

IV. Experiment

The proposed SLAM with independent particle filters for landmark updating and localization is evaluated on 8 HF-band RFID readers with large antennas and RFID-tag textile with 100 tags/m^2 density in the simulation and a real environment. We also verified the FastSLAM method by the 96 readers with the small antennas in the same experiment environment and compared the accuracy of these two methods.



(a) (b)

Fig. 5. The result in the simulation with 8 RFID readers: (a) IC tags (purple points) set in simulation and the fixed trajectory (green lines); (b)detected IC tags (small circles) and path of the robot (red lines) generated by the proposed method.

A. Simulation

The simulation result by our proposed method is shown in Fig. 5. The robot moves along the fixed trajectory 3 times. Figure 5(a) shows the fixed trajectory and positions of IC tags set in the simulation. Figure 5(b) shows the path of the robot and positions of detected IC tags that estimated by the proposed method using the 8-RFID-reader system. Figure 6 shows the path of the robot and positions of detected IC tags generated by FastSLAM using the 96-RFID-reader system. Based on these figures, the path of the robot in Fig. 5(b) is more accurate than Figure 6.

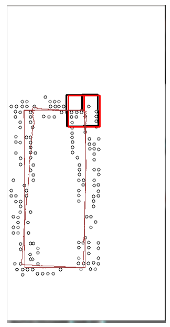


Fig. 6. Path of the robot and positions of the detected IC tags generated by FastSLAM with 96 RFID readers in simulation

TABLE I
SELF-LOCALIZATION ERRORS ON THE FIXED TRAJECTORY IN SIMULATION

	error by Mean			error by Max		
	x [mm]	y [mm]	θ [rad]	x [mm]	y [mm]	θ [rad]
Proposed method (8 readers)	8.3	7.2	0.005	38.4	23.3	0.015
FastSLAM (96 readers)	42.3	10.3	0.018	76.3	45.8	0.051

Table I shows the position and orientation errors of robot generated by our proposed method with 8 RFID readers and FastSLAM with 96 RFID readers. Table II shows the position errors of detected IC tags. Our proposed method shows that the average position errors of the robot are about 8 [mm] in X direction and 7[mm] in Y direction. The average position errors of detected IC tags are about 15.9 [mm] in X direction and 9.8 [mm] in Y direction. FastSLAM shows that the average position errors of the robot are about 42 [mm] in X direction and 10[mm] in Y direction. Average position errors of detected IC tags are about 68 [mm] in X direction and 35[mm] in Y direction. Comparing the results of the proposed method with the ones of FastSLAM, the proposed method is better than FastSLAM in our simulation even though the proposed method uses much fewer RFID readers than the FastSLAM.

As mentioned before, the robot needs to detect the tag in more different directions to narrow the possible area of detected tag while it builds the map by a particle filter.

TABLE II
TAG LOCALIZATION ERRORS ON THE FIXED TRAJECTORY IN SIMULATION

	error by Mean		error by Max	
	x [mm]	y [mm]	x [mm]	y [mm]
Proposed method (8 readers)	15.9	9.8	38.2	38.1
FastSLAM (96 readers)	36.3	11.8	68.0	35.1

TABLE III
TAG LOCALIZATION ERRORS ON THE RANDOM TRAJECTORY IN SIMULATION

	error by Mean		error by Max	
	x [mm]	y [mm]	x [mm]	y [mm]
Proposed method	9.4	9.2	34.2	33.6

Figure 7 shows the comparison between tags located by the proposed method on the random trajectory with the simulation map. Table III shows that the random trajectory offers a better map than the fixed one.

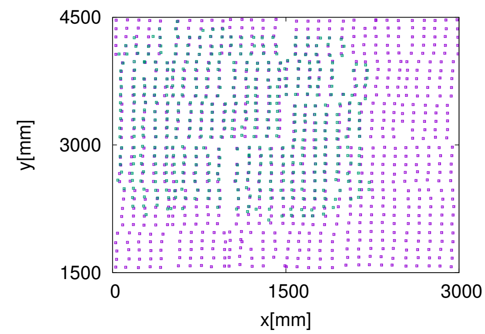


Fig. 7. Comparison between tags located by proposed method on the random trajectory with the simulation map: green points are tags estimated by the proposed method; purple points represent the real position of the tags.

B. Experiment in real environment

Figure 8 shows the real experiment environment. We let the robot moves along a fixed loop trajectory 3 times. Figure 9 shows the path of the robot in ideal state and positions of IC tags set in the real environment. We chose 8 points to check the accuracy of self-localization as Fig 9 shows. Figure 10 shows the path of the robot and the positions of detected IC tags estimated by the proposed method. Figure 11 shows the path of the robot and positions of detected IC tags generated by FastSLAM. The results show that our proposed method performs better than FastSLAM.

Table IV shows the statistics of self-localization errors on the 8 points generated by our proposed method and FastSLAM. Table V shows the errors of tag location. The average position errors of the robot are about 11 [mm] in X direction and 20[mm] in Y direction by our proposed method. This result is better than the one using FastSLAM with the 96-RFID-reader system. The average error of the tag location by using our proposed method become smaller than by using FastSLAM. Because some IC tags were not detected a sufficient number of times, the possible tag location area can not reduce. For a more accurate map of IC tags, the IC tags need to be detected more frequently to make the possible area be smaller.

TABLE IV
SELF-LOCALIZATION ERRORS ON THE FIXED TRAJECTORY IN REAL ENVIRONMENT

	Proposed method			FastSLAM		
	x [mm]	y [mm]	θ [rad]	x [mm]	y [mm]	θ [rad]
error by mean	11.5	20.7	0.043	23.4	52.5	0.027
error by max	27.3	56.7	0.074	58.2	92.8	0.076

So we let the robot run in the experiment area in a random direction. The error data is shown in Table VI. The average

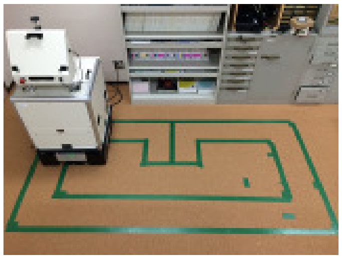


Fig. 8. Experiment environment: green lines are the fixed trajectory

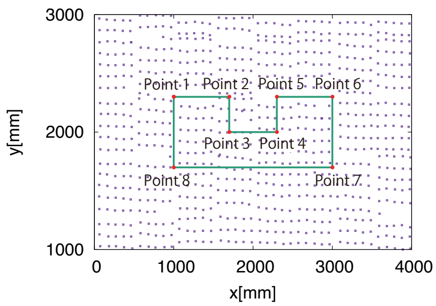


Fig. 9. The configuration of RFID-tag textile with 100 tags/m^2 density set under the floor, the 8 red points mean the chose 8 points to evaluate the accuracy of the robot self-localization.

error doesn't change too much but the largest error becomes smaller.

Comparing our proposed method with FastSLAM in simulation and real environment, our proposed method shows a better result. Besides, we use only 8 RFID readers which could greatly cut down the production cost, compared to the 96 RFID readers system. Moreover, the proposed method solved the problem in the situation of landmark sensing can not be modeled with a Gaussian distribution.

V. CONCLUSIONS

This paper proposed a novel SLAM method in which two particle filters are used for both self-localization and landmark mapping independently and applied it to the multiple RFID readers and multiple tags system. Update of the detected IC tags with Kalman filter is not appropriate because the tag detection range using the large antenna cannot be modeled with a Gaussian distribution. We use particle filters to estimate both the position and orientation of the robot and positions of IC tags. We compared our proposed method with the FastSLAM method and showed our proposed method has much border applicability than FastSLAM. The proposed method has been tested in the simulation and real environment. Whether in simulation or the real environment, the proposed method outperforms FastSLAM.

TABLE V

TAG LOCALIZATION ERRORS ON THE FIXED TRAJECTORY IN REAL ENVIRONMENT

	error by Mean		error by Max	
	x [mm]	y [mm]	x [mm]	y [mm]
Proposed method (8 readers)	37.6	27.9	128.3	156.9
FastSLAM (96 readers)	50.6	46.84	107.3	137.2

TABLE VI

TAG LOCALIZATION ERROR ON THE RANDOM TRAJECTORY IN REAL ENVIRONMENT

	error by Mean		error by Max	
	x [mm]	y [mm]	x [mm]	y [mm]
Proposed method	29.2	36.1	74.0	131.4

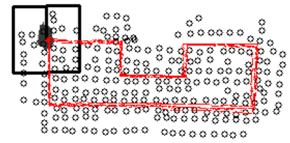


Fig. 10. Path of robot and positions of detected IC tags generated by the proposed method with 8 RFID readers

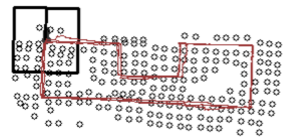


Fig. 11. Path of robot and positions of detected IC tags generated by FastSLAM with 96 RFID readers

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