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## Research Article

# Particle Smoother-Based Landmark Mapping for the SLAM Method of an Indoor Mobile Robot with a Non-Gaussian Detection Model

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HF-band radio-frequency identification (RFID) is a robust identification system that is rarely influenced by objects in the robot activity area or by illumination conditions. An HF-band RFID system is capable of facilitating a reasonably accurate and robust self-localization of indoor mobile robots. An RFID-based self-localization system for an indoor mobile robot requires prior knowledge of the map which contains the ID information and positions of the RFID tags used in the environment. Generally, the map of RFID tags is manually built. To reduce labor costs, the simultaneous localization and mapping (SLAM) technique is designed to localize the mobile robot and build a map of the RFID tags simultaneously. In this study, multiple HF-band RFID readers are installed on the bottom of an omnidirectional mobile robot and RFID tags are spread on the floor. Because the tag detection process of the HF-band RFID system does not follow a standard Gaussian distribution, extended Kalman filter- (EKF-) based landmark updates are unsuitable. This paper proposes a novel SLAM method for the indoor mobile robot with a non-Gaussian detection model, by using the particle smoother for the landmark mapping and particle filter for the self-localization of the mobile robot. The proposed SLAM method is evaluated through experiments with the HF-band RFID system which has the non-Gaussian detection model. Furthermore, the proposed SLAM method is also evaluated by a range and bearing sensor which has the standard Gaussian detection model. In particular, the proposed method is compared against two other SLAM methods: FastSLAM and SLAM methods utilize particle filter for both the landmark updating and robot self-localization. The experimental results show the validity and superiority of the proposed SLAM method.

## 1. Introduction

With the development of self-driving systems, simultaneous localization and mapping (SLAM) technologies based on vision sensors and LiDAR devices are now widely used in outdoor environments. In the SLAM method, self-localization can be performed while simultaneously building an environment map. To allow intelligent robots to better integrate into everyday human life, indoor SLAM technology is also being developed. Vision sensors [1–3] and laser rangefinders (LRFs) [4, 5] are also widely used for the SLAM work of the indoor mobile robots. Vision sensors

are capable of providing visualization environmental maps that can be directly used for other tasks, while LRFs can provide precise range information. However, the vision sensor- and LRF-based approaches often suffer from several types of interference. The visual SLAM requires stable and easy-track visual landmarks which is easily redetectable when the robot passing by a previously visited place. However, visual sensors are easily affected by environmental changes which may lead to the missing recognition for the visual landmarks; in particular, changes in the intensity of light and the movements of objects cause landmarks to be lost or to appear to change. The accuracy of the self-

localization of the robot and map building by utilizing LRFs is easily affected by the unknown moving obstacles around the robot and the transparent walls which are widely used in the current indoor environment.

Unlike visual sensors and LRFs utilized in the indoor mobile robots, radio-frequency identification (RFID) systems employ electromagnetic waves. The communication of the RFID system happens between the RFID reader/writer and IC tags. The RFID system is robust against lighting conditions and the influence of unknown objects around the robot [6–8]. Barcode technology is similar to RFID technology and widely applied in the logistics warehouse. The autonomous delivery robots in the Amazon logistics warehouse navigate around the warehouse by following a series of computerized barcode stickers on the floor. However, it is easily affected by some objects or smudge on the stickers so that they have to keep the floor clean. The characters, SLAM methods, and applications of the sensors mentioned above are listed in Table 1. Although the arrangement of RFID tags is needed, the characters of accurate identification and robust communication are suitable for the self-localization of indoor mobile robots.

The conventional RFID-based self-localization system requires a map which contains the ID information and positions of the IC tags to estimate the location and orientation of the robot. Obtaining the IDs and measuring the positions of IC tags and subsequently building an IC tag map by people are time-consuming and exhausting processes, especially that the RFID-based self-localization system always needs a large number of IC tags for an accurate estimation [17]. Landmark-based SLAM recognizes the natural or artificial characteristic objects in the environment surrounding the robot as landmarks, builds a map of these landmarks, and localizes itself simultaneously. Landmark-based SLAM is useful for the RFID-based self-localization system for the indoor mobile robot by utilizing the IC tags as the landmarks to reduce the labor costs. RFID-based SLAM is capable of providing precise and stable estimation for the localization of the robot and landmarks. Moreover, it can be fused with the vision sensor- and LRF-based SLAM [18] to improve the accuracy of the localization, while obtaining the environmental map to realize feasible navigation for the indoor mobile robot. An RFID IC tag provides a significant advantage owing to its more stable detectability as a landmark. However, the tag detection process of an HF-band RFID system cannot be modeled using a Gaussian distribution which makes the Kalman filter not suitable.

Wang and Takahashi [16] used independent particle filters [19] to achieve both landmark mapping and self-localization for a mobile robot utilizing the HF-band RFID system. To make the article concise, we refer to this SLAM method with the particle filter-based landmark updating as P-SLAM in the following description. The differences between the P-SLAM and FastSLAM with extended Kalman filter (EKF) based landmark updating were also clarified in [16]. In addition, the theoretical and practical superiority of P-SLAM was demonstrated by comparing the method with FastSLAM, using the RFID detection model. However, the particle filter degeneracy problem becomes more serious over time [20].

By adding a Gaussian random value during the motion model updating step for each robot particle at each loop of the SLAM procedure in [16], the degeneration of the particle filter for estimating robot self-localization can be prevented. However, the particles for estimating a stationary landmark are always updated within the states initialized at the first detection of this landmark by using the particle filter in [16]. The tag particles easily converge to a small number of particles at the resampling step and generate the degeneracy problem when using an RFID reader with a large detection range. Utilizing an RFID reader with a large detection is capable of reducing the production cost by decreasing the number of RFID readers and the density of the IC tag set in the environment.

In order to reduce the production cost by increasing the detection range of the RFID reader and suppress the degeneracy problem, we propose to utilize a particle smoother [20, 21] for updating a landmark location in this study. The fixed-lag smoothing method [22, 23] is utilized to estimate the location of the landmark. When a tag is detected multiple times, the particles for estimating this tag are updated by adding a Gaussian random value at each update, which is capable of suppressing the particle degeneracy problem. In particular, the stationary landmark location is estimated based on the historical and current states of the particles so that the estimation becomes more smoothing and accurate. Each detected landmark is updated by an independent particle smoother, which increases the scalability of the proposed system such that it can cope with a large number of landmarks.

The details of the proposed SLAM method with particle filter-based self-localization for mobile robot and particle smoother-based landmark updating are explained in this paper. The proposed method is tested in experiments with different types of conditions. Furthermore, the proposed method is compared against P-SLAM and FastSLAM, using the same experimental environments. The validity and superiority of the proposed method are demonstrated through numerous experiments. This paper is organized as follows. An overview of SLAM approaches with particle filters and smoothers is shown in Section 2. In Section 3, the RFID system and the proposed SLAM method are introduced. In Section 4, we present the results of the experiments. Conclusions are drawn in Section 5.

## 2. Related Work

Vision sensors and LiDAR devices are widely used in current SLAM technologies. However, visual sensors are sensitive to the illumination and dynamic scene and LRFs are also affected by the dynamic objects and transparent materials. RFID sensor utilizes the electromagnetic wave to communication, which is robust against the interference of the dynamic obstacles and illumination conditions. Fetch Robotics has built SICK RFID technology into its TagSurveyor robot, in which logistics providers and retailers can gain data about tagged inventory without requiring handheld or fixed readers. Reverse logistics provider Asset Recovery Specialists monitors the movements of hundreds of pieces of equipment in its San Diego warehouse with an RFID system that detects the zone in which tagged items were last detected,

TABLE 1: Sensors utilized to the SLAM technology of the indoor mobile robot.

Sensors	Monocular	Visual camera Stereo	RGB-D	LRF	Barcode	RFID
Pros	Cheap and useful for indoor and outdoor environment	Available depth information	Directly depth information obtained	High precision and speed	Fast and accurate capture of data	Accurate identification, robust, and cheap
Cons	Scale uncertainty	Complex computation cost and calibration	Large noise and sensitive to outdoor environment	Expensive and sensitive to dynamic object and transparent materials	Need arrangement work and keep visibility and clarity	Arrangement work needed
SLAM method	PTAM [9], ORB-SLAM [10], and LSD-SLAM [11]			Gmapping [12] and cartographer [13]	FastSLAM [14]	RFID-SLAM [15] and P-SLAM [16]
Applications	AR, VR, field robots, and autonomous vehicles			Sweeping robot and autonomous vehicles	Amazon robotics (Kiva)	Internet of things, logistics, and positioning

thereby increasing productivity by 30 percent. The RFID system is effectively applied to logistics and manufacturing in recent years. In this paper, we focus on addressing the problem of an RFID system used for the self-localization of the indoor mobile robot.

According to the working frequency, the RFID system can be divided into different species. RFID systems with low frequency, high frequency, and ultrahigh frequency are always used for the localization of the indoor mobile robot. The traditional RFID-based localization systems are listed in Table 2 and compared with our approach.

Yang et al. [24] proposed a hybrid particle filter method for object tracking by using the UHF-band RFID system. The proposed method is more computationally efficient than the traditional particle filter while providing the same accuracy. However, this method is not able to estimate the orientation of the robot which limits the practicability. Hähnel et al. [25] utilized a UHF-band RFID system with an LRF that is setup on board a mobile robot. A piecewise-constant tag detection sensor model was used to first localize the tags, and then, the map of the tags was used to localize the mobile robot. Joho et al. [26] proposed a probabilistic sensor model characterizing the received signal strength (RSS) information for localizing RFID tags and for tracking a mobile agent. They also assumed that the antenna was localized when building the map of tags and then tracked the mobile agent by utilizing this known tag map. Compared with Hähnel et al. [25] and Joho et al. [26], we locate the RFID tag and mobile agent simultaneously. Kleiner et al. [15] utilized a combination of pedestrian odometry and tag detections to perform graph-based RFID SLAM in a large outdoor environment. However, the long detection range of the UHF-band RFID system also generates great uncertainty and error. Kodaka et al. [27] performed the robot self-localization based on the LF-band RFID system. The localization error was less than 100 mm and 6 deg on average. However, it is difficult in increasing the localization accuracy given the dependence on the size of a tag.

Yang et al. [28] and Mi et al. [29] proposed robot self-localization systems based on the HF-band RFID sensor and significantly improved the precision. An HF-band RFID system is more robust against the influence of environmental changes than the UHF band, which makes it capable of detecting the RFID tags reliably and precisely. Furthermore, the longer communication distance of the HF-band RFID system makes it more suitable than the LF band for the robot localization. An HF-band RFID system is also adopted to our approach. Compared with our research, a pre-coordinated map of RFID tags is needed for both [28, 29]. In particular, both approaches utilized dense tags in the environment which requires a lot of labor costs to build the map of RFID tags manually.

Wang and Takahashi [16] used independent particle filters to achieve landmark mapping and localization for mobile robots based on HF-band RFID. The superiority of P-SLAM is demonstrated through a comparison with FastSLAM using the RFID system. However, in this SLAM method, degeneracy was observed in the particle filter for estimating tag locations. The detection area of the RFID

reader used in [16] was configured as a square with a side length of 60 mm; this small size did not demonstrate that the particle filter degeneracy affects the estimation accuracy obviously. When the detection area of the RFID reader is increased, the effect becomes obvious. Therefore, to solve the degeneracy problem, this paper proposes the use of a particle smoother for updating landmark locations.

The fixed-lag smoothing algorithm, proposed by Kitagawa [22], is based on a storing state vector. The computational cost of this method is almost the same as that of the particle filter. Because the only requirement for fixed-lag smoothing is the memory for storing the particles, the method is relatively fast. A persistent problem is that fixed-lag smoothing cannot use all observations when the number of observations is larger than 10-50. Aside from the fixed-lag smoothing method, researchers have developed alternative methods based on the two-filter formula [30, 31], a forward filtering-backward smoothing formula [32, 33], a maximum posterior sequence estimation [34], and a recursive recomputation approach [35]. However, these methods incur larger computational costs. In order to make the SLAM perform in real time, the fixed-lag smoothing method is adopted in this study.

Berntorp and Nordh proposed the use of Rao-Blackwellized particle smoothing (RBPS) for occupancy-grid based SLAM with an ultrasound sensor [36]. The authors implemented an RBPS for jointly estimating the position of the robot and the map. A more effective map model that incorporates the uncertainty of the measurements was used in this approach. The proposed method was verified on a Lego Mindstorms mobile robot with low-performance motors and a low-cost ultrasonic range finder. The experimental results show that the smoothing substantially improved robustness and increased the predictability of the proposed algorithm. However, each particle contains an estimate of the entire map in [36], which significantly increases memory requirements. The computational demands of smoothing are also greater than those of filtering. As a result, the memory requirements and computational costs will be prohibitive when handling larger maps. In our proposed method, each landmark is updated by a set of particles using the fixed-lag smoothing method. The computational costs of this method are almost the same as those of the particle filter. The only requirement is the memory for storing the particles.

Clark et al. developed a random finite set approach to SLAM by introducing forward-backward smoothing to refine vehicle trajectories [37]. The algorithms were implemented using sequential Monte Carlo and Gaussian mixture techniques. The proposed method was evaluated in a simulated environment with a range and bearing detection model. In this scenario, the uncertainty in the vehicle position distribution increases as the vehicle traverses the path; when the loop is closed, the uncertainty decreases. By smoothing backwards at times immediately prior to the loop closure, a significant reduction in estimated vehicle positions is achieved. In a similar manner as in [37], we propose using a smoother to refine the estimation of landmarks. Our proposed method is not only suitable for the non-Gaussian RFID detection model but also can be used with other models. The validity of the

TABLE 2: Related works: an RFID-based localization system.

Works	Sensors	Dense of tags	Manually built tag map	Robot localization	Tag localization	SLAM	Precision (mm)
Yang et al. [24]	UHF-RFID	9 tags/m <sup>2</sup>	✓	Hybrid particle filter	✗	✗	186
Hähnel et al. [25]	UHF-RFID+LRF	Attached to objects	✗	Monte Carlo localization (with known tag position)	Particle filter (with known robot route)	✗	Much better than only using a laser
Joho et al. [26]	UHF-RFID	350 tags	✗	Monte Carlo localization (with known tag position)	Particle filter (with known robot route)	✗	355
Kleiner et al. [15]	UHF-RFID +odometry	10tags/90,000 m <sup>2</sup>	✗	Graph optimization	Graph optimization	✓	5,640
Kodaka et al. [27]	LF-RFID	Lattice, 16 tags/m <sup>2</sup>	✓	Particle filter	✗	✗	<100
Yang and Wu [28]	HF-RFID	100 tags/m <sup>2</sup>	✓	Particle filter	✗	✗	53
Mi and Takahashi [29]	HF-RFID	100 and 16 tags/m <sup>2</sup>	✗	Monte Carlo localization	✗	✗	25 and 22
Wang and Takahashi [16]	HF-RFID	100 and 16 tags/m <sup>2</sup>	✗	Particle filter	Particle filter	✓	14.5 and 21 (with detection range of 30)
Our approach	HF-RFID	4 tags/m <sup>2</sup>	✗	Particle filter	Particle smoother	✓	>25 and <55 (with detection range from 50 to 250)

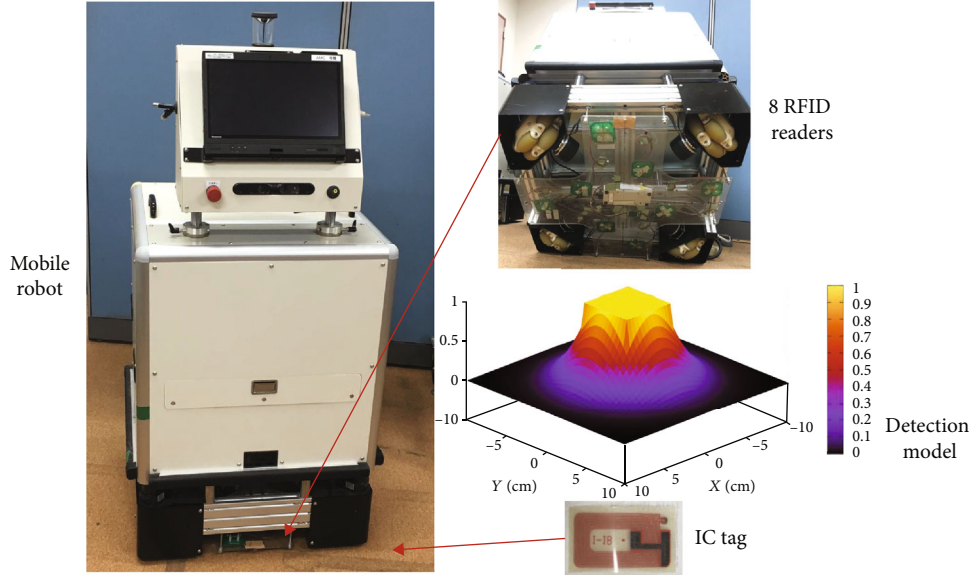


FIGURE 1: An RFID system utilized for the indoor mobile robot in this research.

proposed method is also evaluated using a range and bearing detection model.

### 3. SLAM Method for an Indoor Mobile Robot Based on an HF-Band RFID System

**3.1. HF-Band RFID System Utilized for an Indoor Mobile Robot.** The HF-band RFID system applied to the indoor mobile robot used in our study is shown in Figure 1. Multiple RFID readers are installed on the bottom of the robot. The size of one RFID reader antenna in Figure 1 is  $60 \times 60 \text{ mm}^2$ . The detection range of the RFID reader is almost the same with this size. In particular, the detection model of the RFID reader is close to a step function. IC tags are embedded in the carpets and spread on the floor. The size of the passive IC tag is  $10 \times 20 \text{ mm}^2$ . Each IC tag is assigned with a unique ID, and the distribution of these IC tags is unknown when they are spread on the floor. The robot localization can be achieved with known IC tag IDs and positions. However, measuring the positions and recording the ID information of IC tags require a significant amount of labor and time. SLAM is a sensible method for solving this problem. In this study, IC tags are used as landmarks in the SLAM system. The robot localizes itself by using RFID readers to recognize the IC tags spread on the floor and estimates the locations of the detected IC tags simultaneously during movement.

**3.2. Prior Knowledge of RFID-Based SLAM.** From a probabilistic perspective, the RFID-based SLAM problem can be written in the factored form:

$$p(w_{x_t}, w_{m_{1:N}} | z_t, u_t, n_t) = p(w_{x_t} | z_t, u_t, n_t) p(w_{m_{1:N}} | w_{x_t}, z_t, u_t, n_t), \quad (1)$$

where  $w_{x_t} = (w_x, w_y, w_\theta)$  is the pose of the robot at time  $t$ ,  $w_{m_{1:N}}$  denotes the map of the tags built during the movement,

$N$  is the number of tags spread in the environment,  $z$  is the observation,  $u$  is the robot control, and  $n$  is the index of the detected tag.

FastSLAM uses a particle filter to estimate the robot pose of the first term in the posterior in equation (1). A separated estimator is used to estimate the location of each tag in  $m$ . The estimated robot pose and the parameters express the tag locations are contained in one particle. Each particle in FastSLAM is of the form

$$y_t^{[k]} = \left\langle w_{x_t}^{[k]}, \omega_t^{[k]}, \mu_{1,t}^{[k]}, \sum_{1,t}^{[k]}, \dots, \mu_{N,t}^{[k]}, \sum_{N,t}^{[k]} \right\rangle, \quad (2)$$

where  $y_t^{[k]}$  is the combined state vector of the robot pose and the map of RFID tags.  $w_{x_t}^{[k]}$  is the pose of the robot in the world coordinate system represented by particle  $[k]$ .  $\omega_t^{[k]}$  denotes the importance weight of particle  $[k]$ .  $\mu_{n,t}^{[k]}$  and  $\sum_{n,t}^{[k]}$  are the center vector and the covariance matrix, which used to present the location of the tags. The location parameters of the tags are updated by an EKF. FastSLAM is capable of using a case of the likelihood model for tag detection, which can be modeled as a Gaussian distribution. The detection model of an HF-band RFID reader is modeled as shown in Figure 1, and it does not belong to a Gaussian distribution. Therefore, FastSLAM is not appropriate to the SLAM task based on the HF-band RFID system with the non-Gaussian detection model.

Particle filter does not need any parametric model so that it is suitable to estimate a non-Gaussian state. P-SLAM [16] used the particle filter to estimate both the robot localization and tag locations. In P-SLAM,  $1 + N$  particle filters are used to estimate the pose of the robot and  $N$  tag locations. One particle filter is used to estimate

the position and orientation of the robot. Each robot particle is of the form

$$\mathbf{y}_{r,t}^{[i]} = \langle w \mathbf{x}_t^{[i]}, \boldsymbol{\omega}_t^{[i]} \rangle, \quad (3)$$

where  $[i]$  is the index of the robot particle, and  $\mathbf{y}_{r,t}^{[i]}$  is the state vector of robot particle  $[i]$ .  $N$  particle filters are used to estimate the positions of  $N$  detected tags. The particle filters are independent of each other. Each tag particle is of the form

$$\tilde{\mathbf{y}}_n^{[j]} = \langle w \mathbf{m}_n^{[j]}, \boldsymbol{\omega}_n^{[j]} \rangle, \quad (4)$$

where  $\tilde{\mathbf{y}}_n^{[j]}$  is the state vector of tag particle  $[j]$  in P-SLAM.  $w \mathbf{m}_n^{[j]} = (w x_n, w y_n)$  is the position of tag  $n$  in the world coordinate system represented by tag particle  $[j]$ .  $\boldsymbol{\omega}_n^{[j]}$  is the importance weight of tag particle  $[j]$ .

However, the degeneracy of the particle filter for estimating a stationary tag location becomes serious over time, which may result in irreversible tag location errors. In order to avert this problem, we propose utilizing a particle smoother for each landmark updating.

**3.3. Particle Fixed-Lag Smoother.** The smoothing distribution of the particles can be represented sequentially as

$$p(\mathbf{x}_{0:t} | \mathbf{z}_{1:t}) \propto p(\mathbf{x}_{0:t-1} | \mathbf{z}_{1:t-1}) h(\mathbf{z}_t | \mathbf{x}_t) f(\mathbf{x}_t | \mathbf{x}_{t-1}), \quad (5)$$

where  $\mathbf{x}_{0:t}$  is the path of the robot and  $\mathbf{z}_t$  means the observations obtained during the robot movements.  $f(\mathbf{x}_t | \mathbf{x}_{t-1})$  and  $h(\mathbf{z}_t | \mathbf{x}_t)$  are, respectively, the specified state function and observation function. The sequential character appears clearly when this equation is decomposed into a prediction step,

$$p(\mathbf{x}_{0:t} | \mathbf{z}_{1:t-1}) = p(\mathbf{x}_{0:t-1} | \mathbf{z}_{1:t-1}) f(\mathbf{x}_t | \mathbf{x}_{t-1}), \quad (6)$$

and an analysis step,

$$p(\mathbf{x}_{0:t} | \mathbf{z}_{1:t}) \propto p(\mathbf{x}_{0:t} | \mathbf{z}_{1:t-1}) h(\mathbf{z}_t | \mathbf{x}_t). \quad (7)$$

The particle fixed-lag smoother, which was proposed by Kitagawa, can be achieved through a simple extension to the particle filter as shown in [22]. The difference lies in the fact that the size of the state vector to be estimated is kept stationary in the last  $L$  time steps. Consequently, the oldest state is ruled out from the estimation process at each prediction step. The prediction step becomes

$$p(\mathbf{x}_{t-L+1:t} | \mathbf{z}_{1:t-1}) = f(\mathbf{x}_t | \mathbf{x}_{t-1}) \int p(\mathbf{x}_{t-L+1:t-1} | \mathbf{z}_{1:t-1}) d\mathbf{x}. \quad (8)$$

This smoother is straightforward to implement and incurs a negligible CPU cost similar to that of the particle

filter. However, the diversity of the particles in the state vector representing the smoothing distribution decreases with a large  $L$ ; as a result, the smoothing distribution cannot be approximated correctly. In order to avert this problem,  $L$  is constantly set at 20 to 30 based on [38].

**3.4. SLAM Based on Particle Smoother for Landmark Mapping and Particle Filter for Robot Self-Localization.** The proposed SLAM method utilizes one particle filter to estimate the pose of the robot and  $N$  particle fixed-lag smoothers to estimate the positions of the RFID tags. The form of the robot particle is the same as equation (3). Each detected RFID tag is estimated by an independent particle smoother. Each tag particle in the particle smoother is of the form

$$\mathbf{y}_{n,t}^{[c]} = \langle w \mathbf{m}_{n,t}^{[c]}, \widehat{\mathbf{S}}_{n,t}^{[c]}, \boldsymbol{\omega}_{n,t}^{[c]} \rangle, \quad (9)$$

where  $\mathbf{y}_{n,t}^{[c]}$  is the state vector of tag particle  $[c]$  used to estimate the location of tag  $n$  in the proposed SLAM method.  $w \mathbf{m}_{n,t}^{[c]} = (w x_{n,t}, w y_{n,t})$  is the position parameter of tag particle  $[c]$ .  $\widehat{\mathbf{S}}_{n,t}^{[c]}$  is the set that records the value from  $w \mathbf{m}_{n,t-L+1}^{[c]}$  to  $w \mathbf{m}_{n,t}^{[c]}$ . The importance weight of tag particle  $[c]$  is represented by  $\boldsymbol{\omega}_{n,t}^{[c]}$ .

Algorithm 1 presents the algorithm of our proposed SLAM method which utilizes a particle filter for the robot localization and  $N$  independent particle smoothers for the landmark updating. The robot starts with a known position and orientation. The particles for estimating the robot localization are initially distributed around this start spot. The parameters of the position and orientation of these robot particles are updated by the motion model at each loop of the SLAM procedure. The motion model is defined as

$$w \mathbf{x}_t = w \mathbf{x}_{t-1} + \mathbf{v} \Delta t + \boldsymbol{\varepsilon} \Delta t, \quad \boldsymbol{\varepsilon} \sim N(0, \sigma), \quad (10)$$

where  $\mathbf{v} = (v_x, v_y, \boldsymbol{\omega})$  and  $\Delta t$  are the velocity of the robot and the period between times  $t-1$  and  $t$ , respectively.  $N(0, \sigma)$  denotes the Gaussian distribution with the standard deviation  $\sigma$ .

When a tag is detected by the robot, the robot firstly determines whether this tag has been detected before by its ID. If this tag is detected for the first time, a novel tag particle set is assigned to this tag for estimating its location. These tag particles are distributed around the RFID reader that detected this tag and the importance weight of these tag particles are assigned with value 1. Moreover, the initial position parameters of these particles are stored in their respective set of  $\widehat{\mathbf{S}}_n^{[c]}$  used for the following step of smoothing procedure. Otherwise, the position parameters of the tag particles for estimating the detected IC tag  $n$  are updated by adding a Gaussian random value in line 11 to suppress the degeneracy problem. Then, the updated position parameters are used to calculate the importance weight of each tag particle with



```

1: Initialize robot particles  $\mathcal{S}_{r,t} = (\mathbf{y}_{r,t}^{[1]}, \mathbf{y}_{r,t}^{[2]}, \dots, \mathbf{y}_{r,t}^{[l]})$ 
2: for  $i = 1$  to  $l$  do
3:   Update particles with the motion model:  $w \mathbf{x}_t^{[i]} = \text{MotionModel}(w \mathbf{x}_{t-1}^{[i]})$ 
4: end for
5: if tag  $n$  is detected then
6:   if tag  $n$  is detected for the first time then
7:     Initialize tag particles  $\mathcal{S}_{n,t} = (\mathbf{y}_{n,t_0}^{[1]}, \mathbf{y}_{n,t_0}^{[2]}, \dots, \mathbf{y}_{n,t_0}^{[c]})$ 
8:     Store  $w \mathbf{m}_{n,t_0}^{[c]}$  in  $\widehat{\mathcal{S}}_{n,t_0}^{[c]}$ 
9:   else
10:    for From  $c = 1$  to  $C$  do
11:      Obtain  $w \mathbf{m}_{n,t}^{[c]}$  based on  $w \mathbf{m}_{n,t-1}^{[c]}$  with a Gaussian random value
12:      Update  $\omega_{n,t}^{[c]}$  on the basis of the likelihood function
13:      Store  $w \mathbf{m}_{n,t}^{[c]}$  in  $\widehat{\mathcal{S}}_{n,t}^{[c]}$ 
14:    end for
15:   end if
16:   for From  $c = 1$  to  $C$  do
17:     Draw  $k$  with probability  $\propto w_{n,t}^{[k]}$ 
18:     Add  $\bar{\mathbf{y}}_{n,t}^{[k]}$  to  $\bar{\mathcal{S}}_{n,t}$ 
19:   end for
20:    $\mathcal{S}_{n,t} \leftarrow \bar{\mathcal{S}}_{n,t}$ 
21:   for From  $c = 1$  to  $C$  do
22:      $w \tilde{\mathbf{m}}_{n,t}^{[c]} = \sum_{o=t+1-L}^t w \mathbf{m}_{n,o}^{[c]} / L$ 
23:   end for
24:   Update  $w \tilde{\mathbf{x}}_n$  based on  $w \tilde{\mathbf{m}}_{n,t}^{[c]}$  and  $\omega_{n,t}^{[c]}$ 
25:   for From  $i = 1$  to  $l$  do
26:     Update  $\omega_t^{[i]}$  on the basis of the likelihood function
27:   end for
28: end if
29: for  $i = 1$  to  $l$  do
30:   Draw  $k$  with probability  $\propto \omega_t^{[i]}$ 
31:   Add  $\bar{\mathbf{y}}_{r,t}^{[k]}$  to  $\bar{\mathcal{S}}_{r,t}$ 
32: end for
33:  $\mathcal{S}_{r,t} \leftarrow \bar{\mathcal{S}}_{r,t}$ 
34: return  $\mathcal{S}_{r,t}, \mathcal{S}_{n,t}$ 

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ALGORITHM 1: SLAM based on particle smoother for landmark mapping and particle filter for self-localization.

index  $n$  based on the likelihood function. The likelihood function is defined based on the HF-band RFID detection model. Figure 2 shows the likelihood distribution of the RFID detection model.

Likelihood function is expressed as a piecewise function as

$$\omega = \begin{cases} 1, & \text{if } |{}^r x_n - {}^r x_a| < \sigma, |{}^r y_n - {}^r y_a| < \sigma, \\ \gamma \exp\left(-\frac{1}{2\sigma^2} ({}^r \mathbf{x}_n - {}^r \mathbf{x}_a)^\top ({}^r \mathbf{x}_n - {}^r \mathbf{x}_a)\right), & \text{else,} \end{cases} \quad (11)$$

where  ${}^r \mathbf{x}_n = ({}^r x_n, {}^r y_n)^\top$  and  ${}^r \mathbf{x}_a = ({}^r x_a, {}^r y_a)^\top$  are the coordinates of the detected IC tag  $n$  and the reader  $a$  detects this tag in the robot coordinate system, respectively.  $\sigma$  is set using the half value of the detection range, and  $\gamma$  is a constant. The updated position parameters of each tag particle

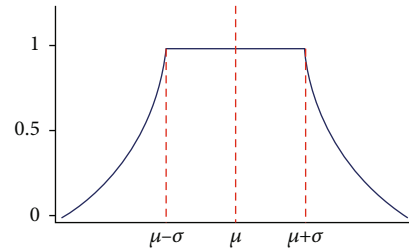


FIGURE 2: Likelihood model for tag detection.

for estimating tag  $n$  are also stored in its set of  $\widehat{\mathcal{S}}_n^{[c]}$ . At the resampling step, a new distribution of the tag particles for estimating tag  $n$  is generated based on the importance weights obtained in line 12 of Algorithm 1. Then, the smoothed distribution of the tag particles for estimating

tag  $n$  is obtained by calculating the average value of  $m_n^{[c]}$  from  $t+1-L$  to  $t$ , which were stored in  $\hat{\mathcal{S}}_n^j$  of each tag particle. The location of tag  $n$  is lastly estimated based on this average value  $w\tilde{m}_{n,t}^{[c]}$  and the importance weight  $\omega_{n,t}^{[c]}$  of each tag particles with index  $n$ .

After estimating the location of the detected IC tag, the position and orientation of the robot are estimated by the robot particles by using the particle filter. The updated location of the detected IC tag is utilized as the observation to calculate the importance weight of each robot particle based on the likelihood function of equation (11) as shown in line 26 of Algorithm 1. The distribution of the robot particles is transformed at the resampling step based on the updated importance weights. Finally, the position and orientation of the robot are estimated based on the resampled robot particles. Then, the procedure is repeated.

**3.5. The Validity and Superiority of the Proposed SLAM Method.** To demonstrate the validity and superiority of our proposed SLAM method, it was compared with P-SLAM and FastSLAM in time cost and accuracy in a simulated environment. The simulated environment is set with the IC tags with the density of 4 tags/m<sup>2</sup>. Eight RFID readers are installed on the bottom of the robot.

The simulated environment is built by using a PC with a 2.6 GHz CPU.

Firstly, three SLAM methods were evaluated by utilizing a different number of particles for estimating the robot localization. The robot particles of our proposed SLAM method and P-SLAM and the particles of FastSLAM were set from 100 to 5000. Both the proposed SLAM method and P-SLAM method used 100 tag particles for estimating a detected IC tag. The robot run along a predefined trajectory. The average time costs of an update of three SLAM methods were calculated after the movement. The average time costs of an update of three SLAM methods with the different number of robot particles are shown in Figure 3(a). For all three methods, the average time cost increases as the number of robot particles increases. However, the increased rate of the time cost utilizing FastSLAM is much faster than the increased rates of our proposed SLAM and P-SLAM. Although more parameters are stored in the tag particle of the proposed SLAM, the average time cost of an update of the proposed SLAM method is basically the same with P-SLAM.

We subsequently investigated how an increase in the number of detected tags would affect the time cost of an update in all three methods. The robot also run along a predefined trajectory. The average time costs of an update of three SLAM methods at the different number of detected IC tags were calculated after the movement. Figure 3(b) shows the results of the times costs of three SLAM methods at the different number of detected IC tags. The time cost of FastSLAM shows a linear growth trend as the number of detected RFID tags increases. The time costs using the proposed SLAM method and P-SLAM are substantially unchanged and much smaller than those of FastSLAM. By using our proposed SLAM method and P-SLAM, each

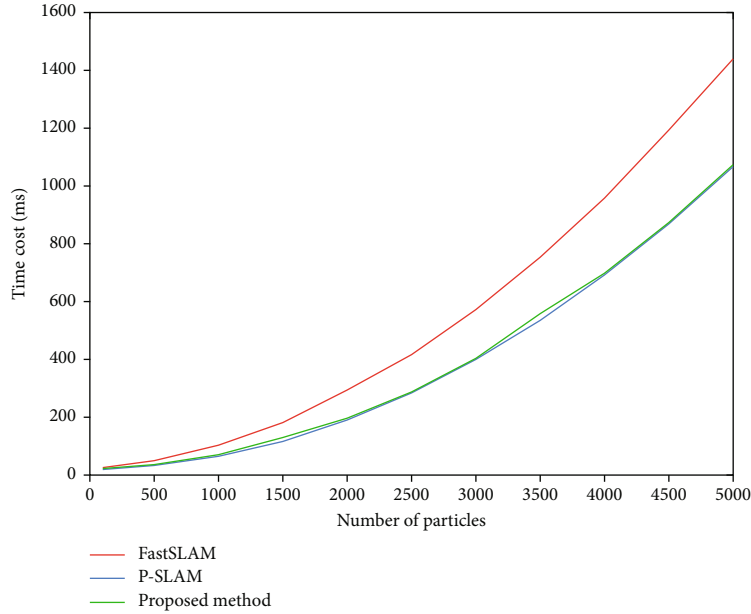
tag is, respectively, estimated by an independent particle filter and particle smoother so that the time cost of an updating is not affected by the increase of the detected tags. The proposed method incurs almost the same time cost as the P-SLAM.

Finally, we evaluated the accuracy of three SLAM methods by using different detection ranges of the RFID reader. The detection range was set from 100 to 500 mm. The robot run on five predefined trajectories with each detection range. On each trajectory, the robot moved in three loops. Figure 4 shows the average robot and tag location errors generated by these three SLAM methods on the five predefined trajectories with different detection ranges. The accuracy of the robot and tag locations decreases with increases in the detection range. Because the RFID detection model does not belong to a Gaussian model, a large detection range brings increased uncertainty and noise. According to the results, the errors generated by FastSLAM are significantly larger than those generated by the other two methods, particularly when the detection range increases. The accuracies of the proposed method and P-SLAM are very similar when the detection range is less than 180 mm. However, the performance of the proposed method becomes better than that of P-SLAM as the detection range continues to increase. This proves that the proposed method is more suitable for non-Gaussian detection model sensors with large detection ranges. When a particle filter is used to estimate the tag location, particles easily converge to an incorrect location with rapid degeneracy. A particle smoother allows the particles to converge slowly and obtains a stable estimation, which improves the accuracy of full SLAM tasks.

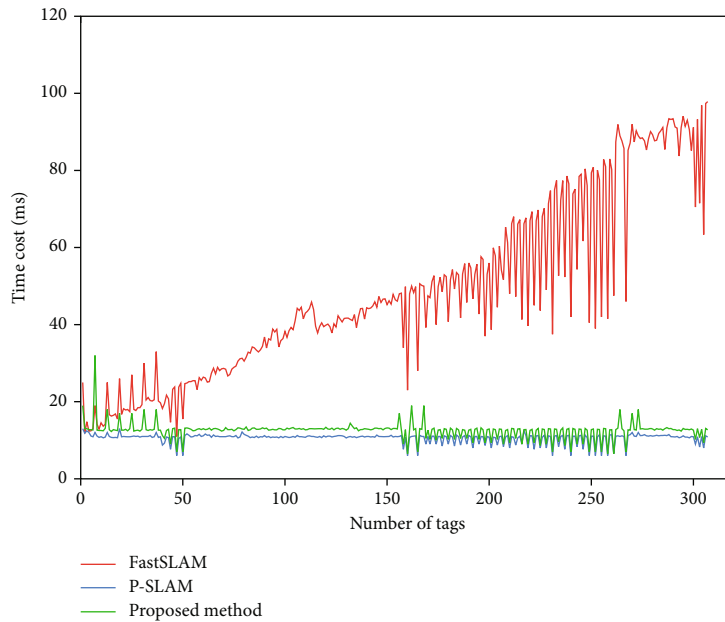
According to the evaluations in time cost and accuracy mentioned above, although the proposed method utilizes the particle smoother which requires more memory than particle filter for estimating the tag location, the time cost of the proposed SLAM method is almost the same as that of the P-SLAM and much smaller than FastSLAM. In particular, the proposed SLAM method got a better performance in accuracy than P-SLAM and FastSLAM by using an RFID reader with the large detection range.

## 4. Experiment

The proposed SLAM method which utilizes the particle smoother for landmark updating was evaluated in more experiments using the HF-band RFID detection model and a range and bearing sensor detection model. Using the HF-band RFID detection model, we tested the proposed method with three types of movement trajectories: a predefined trajectory without rotation, a predefined trajectory with rotation, and an unspecified trajectory. When the robot moved on a predefined trajectory, the path estimated by the SLAM method was easily compared with the predefined trajectory; this made it relatively easy to evaluate the performance of the robot self-localization. When the robot moved on an unspecified trajectory, it moved a longer distance and detected more tags to evaluate the stability and accuracy of the proposed method. The proposed SLAM method evaluated by the range and bearing sensor was operated on two types of predefined trajectories: with rotation and without



(a)

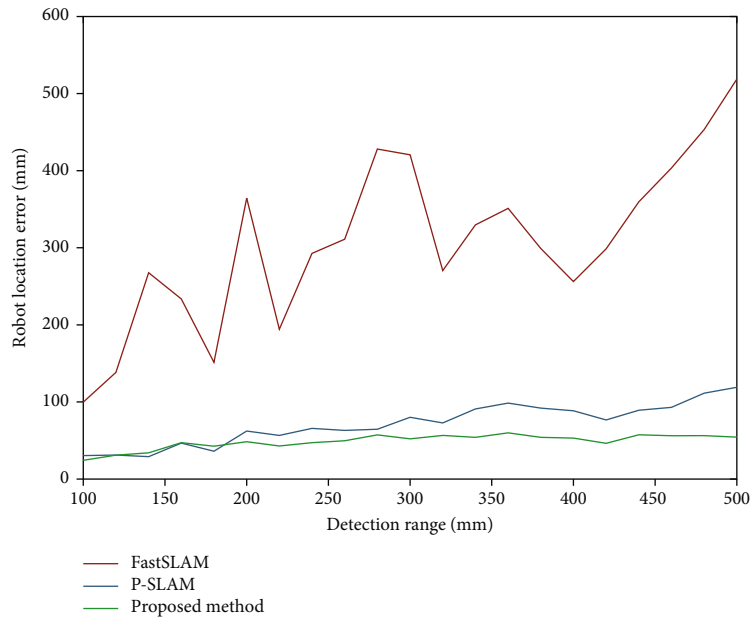


(b)

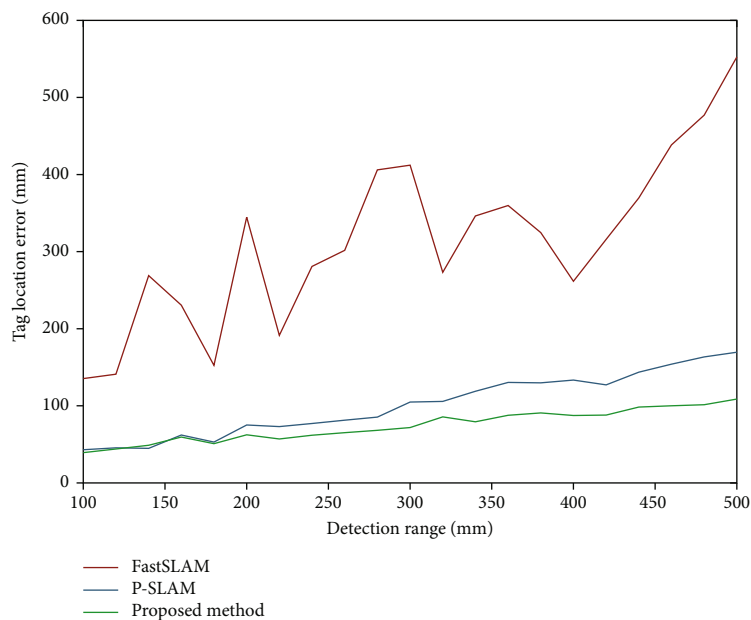
FIGURE 3: Average time costs of an update of the proposed SLAM method, P-SLAM, and FastSLAM with (a) a different number of robot particles and (b) a different number of detected tags.

rotation. Moreover, five different trajectories were utilized in the predefined trajectory experiments for both sensor model types. Using the same experimental environment, we also evaluated the P-SLAM and FastSLAM, in order to compare them against our proposed method. The average errors of the robot and tag location were used to evaluate the three SLAM methods mentioned above. We assigned 500 particles to FastSLAM. Our proposed SLAM method and P-SLAM utilized 500 robot particles and 100 tag particles in the experiments.

*4.1. Experiment with the HF-Band RFID Detection Model.* The proposed method was evaluated with eight HF-band RFID readers installed on the bottom of the mobile robot. The detection range of the RFID reader was set at 300 by 300 mm<sup>2</sup> ( $\sigma = 150$  mm). The detection range of the RFID reader used in [16] was set at 60 by 60 mm<sup>2</sup>. By using a large detection range, a type of the RFID-tag textile with a density of 4 tags/m<sup>2</sup> was used in this study which reduces the production cost than [16] that utilized types of the RFID-tag textile with the densities of 100 and 16 tags/m<sup>2</sup>.



(a)



(b)

FIGURE 4: (a) Average robot location errors by the proposed method, P-SLAM, and FastSLAM, using different detection ranges. (b) Average tag location errors by the proposed method, P-SLAM, and FastSLAM, using different detection ranges.

#### 4.1.1. Predefined Trajectory without Rotation Experiment.

The robot equipped with eight RFID readers moved along five predefined trajectories without rotation to estimate the robot self-localization and tag locations to evaluate the proposed SLAM method, P-SLAM, and FastSLAM. The robot runs on each predefined trajectory three loops. We only show figures of the results of three SLAM methods on one predefined trajectory here to avoid a lengthy article. Figure 5 shows the results of the proposed SLAM method, P-SLAM, and FastSLAM on one trajectory. Figure 5 shows that the path of the robot and the tag loca-

tions estimated by the proposed SLAM method is more accurate than that estimated by P-SLAM and FastSLAM. The path of the robot estimated by FastSLAM has incorrect estimations both on the position and orientation, and the tag locations are also incorrectly estimated, as shown in Figure 5(a). The path of the robot and tag positions estimated by P-SLAM offsets to the right as presented in Figure 5(b). Figure 5(c) shows that the robot path estimated by the proposed SLAM method almost coincides the predefined trajectory and most of the tags overlap with the ground truth.

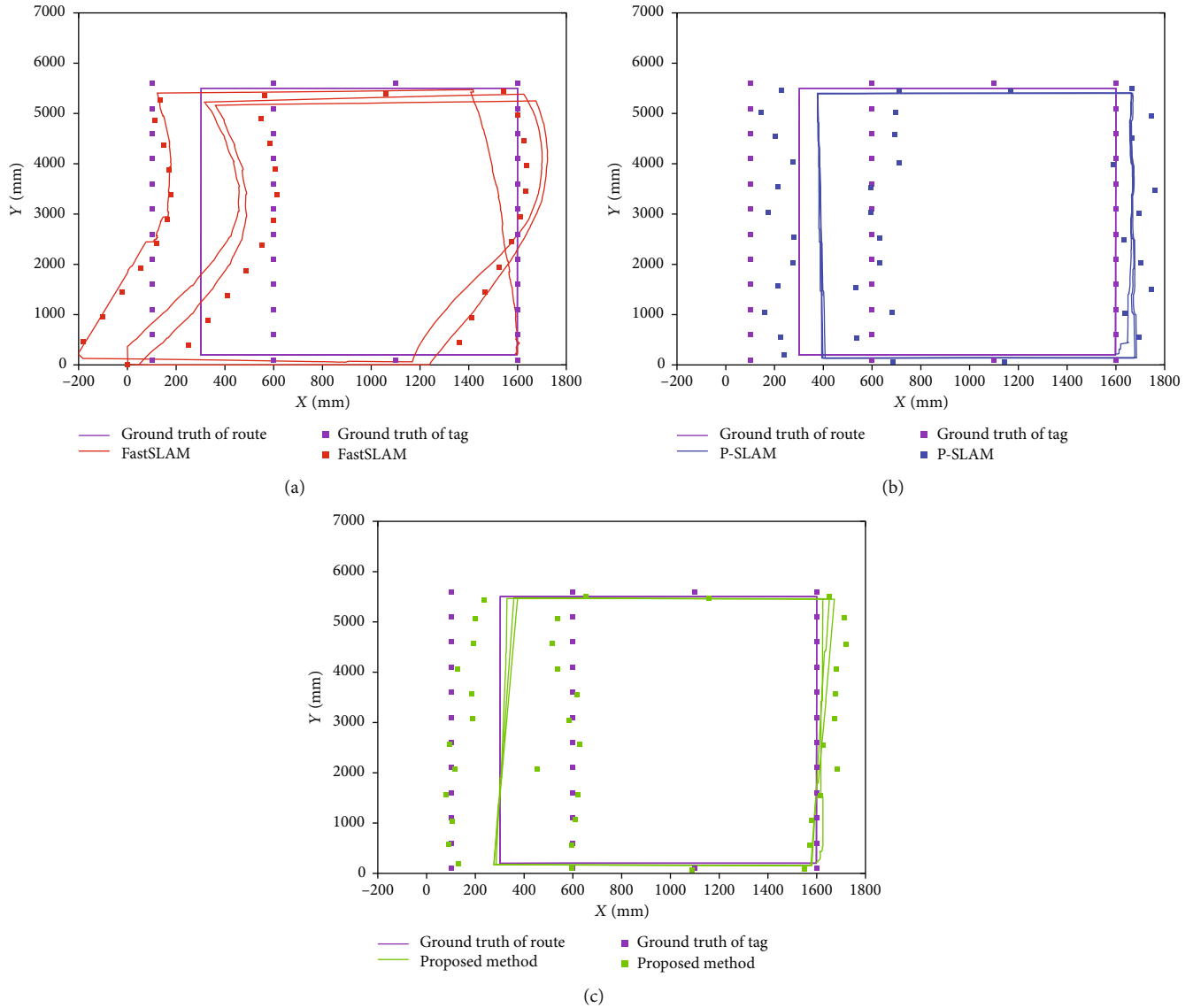


FIGURE 5: Results obtained by FastSLAM, P-SLAM, and the proposed method, using the RFID detection model on a predefined trajectory without rotation. (a), (b), and (c), respectively, show the results obtained by FastSLAM, P-SLAM, and the proposed method.

Table 3 presents the average errors of the robot self-localization and tag locations obtained by the proposed SLAM method, P-SLAM, and FastSLAM on the five predefined trajectories without rotation. The average distance errors of the robot self-localization and tag locations are 54 mm and 79 mm by using our proposed SLAM method. The average orientation error of the robot self-localization is 0.006 rad. The results obtained by the proposed SLAM method are sufficiently precise for the robot self-localization and tag locations taking into account the detection range and the interval of the IC tags. The localization errors generated by P-SLAM are smaller than that generated by FastSLAM. However, comparing the results of P-SLAM with our proposed SLAM method, the distance errors generated by P-SLAM are much larger than that generated by our proposed SLAM method in the same situation. The proposed SLAM method exhibited the best performance

on the predefined trajectory without rotation by using the HF-band RFID detection model.

**4.1.2. Predefined Trajectory with Rotation Experiment.** The robot with eight HF-band RFID readers moved along five predefined trajectories with rotation to estimate the robot self-localization and tag locations to evaluate the proposed SLAM method, P-SLAM, and FastSLAM. The paths of the robot and tag locations estimated by the proposed SLAM method, P-SLAM, and FastSLAM on one predefined trajectory with rotation are shown in Figure 6. Figure 6 shows the same performance as that shown in Figure 5; that is, the results obtained by the proposed method are superior to those estimated by FastSLAM and P-SLAM. The path of the robot and tag positions estimated by FastSLAM largely deviate from the ground truth, as shown in Figure 6(a). Figure 6(b) shows that the estimation obtained

TABLE 3: Errors of the robot and tag localization generated by FastSLAM, P-SLAM, and the proposed SLAM method, using the RFID detection model on predefined trajectories without rotation.

Method	Robot location				Tag location		
	$x$ (mm)	$y$ (mm)	$\theta$ (rad)	$d_r$ (mm)	$x$ (mm)	$y$ (mm)	$d_t$ (mm)
FastSLAM	315.1	204.5	0.182	420.8	296.6	210.1	412.1
P-SLAM	41.4	66.6	0.003	82.1	66.1	80.1	110.5
Proposed method	25.4	45.1	0.006	53.8	50.3	51.2	79.0

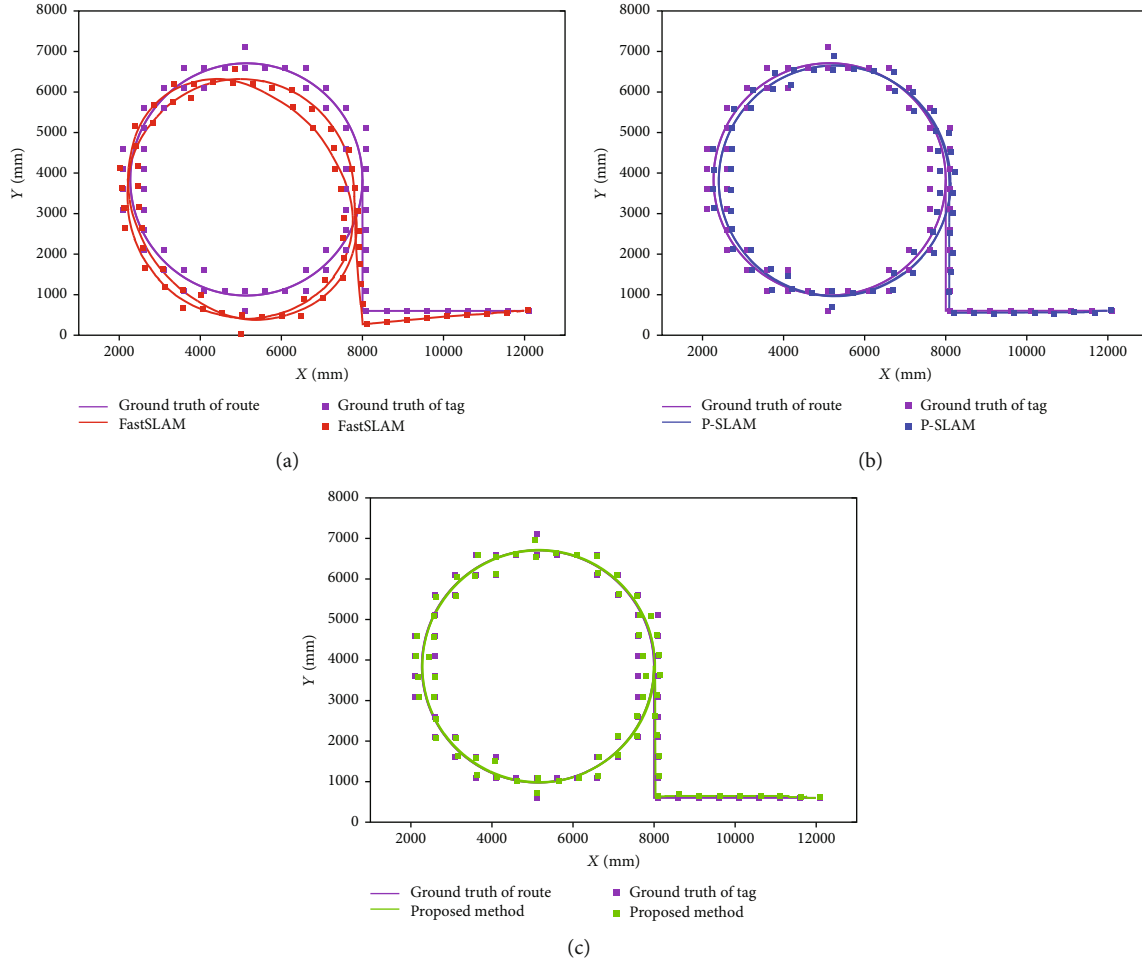


FIGURE 6: Results obtained by FastSLAM, P-SLAM, and the proposed method, using the RFID detection model on a predefined trajectory with rotation. (a), (b), and (c), respectively, show the results obtained by FastSLAM, P-SLAM, and the proposed method.

by P-SLAM is more accurate than that of FastSLAM. However, the path of the robot and the location of the detected tags estimated by the proposed method almost overlap with the ground truth, as shown in Figure 6(c); as can be seen, the results are better than those shown in Figure 6(b).

Table 4 lists the average errors of the robot self-localization and the tag locations on five different trajectories with rotation, as generated by our proposed method, P-SLAM, and FastSLAM. For the proposed method, the average position error of the robot is approximately 36 mm and the average rotation error of the robot is 0.005 rad, while the average position errors of the detected RFID tags are approx-

imately 66 mm. In contrast, the average position errors of the robot and tags estimated by FastSLAM exceed 300 mm, which fully proves that FastSLAM is not suitable for the HF-band RFID detection model. Although the results obtained by the P-SLAM method were better than those of FastSLAM, our proposed method obtained the best overall performance.

**4.1.3. Unspecified Trajectory Experiment.** As discussed in [16], when using P-SLAM, the distribution of particles for estimating a detected tag can be effectively modified by letting the robot detects this tag in additional alternative directions to obtain more observations; this step helps improve the accuracy of the tag location and robot self-localization.

TABLE 4: Errors of the robot and tag localization generated by FastSLAM, P-SLAM, and the proposed SLAM method, using the RFID detection model on predefined trajectories with rotation.

Method	Robot location				Tag location		
	$x$ (mm)	$y$ (mm)	$\theta$ (rad)	$d_r$ (mm)	$x$ (mm)	$y$ (mm)	$d_t$ (mm)
FastSLAM	147.9	266.5	0.063	330.4	134.3	254.06	311.9
P-SLAM	74.3	36.8	0.005	86.6	81.2	52.7	104.6
Proposed method	23.9	22.7	0.005	36.2	41.9	41.0	65.7

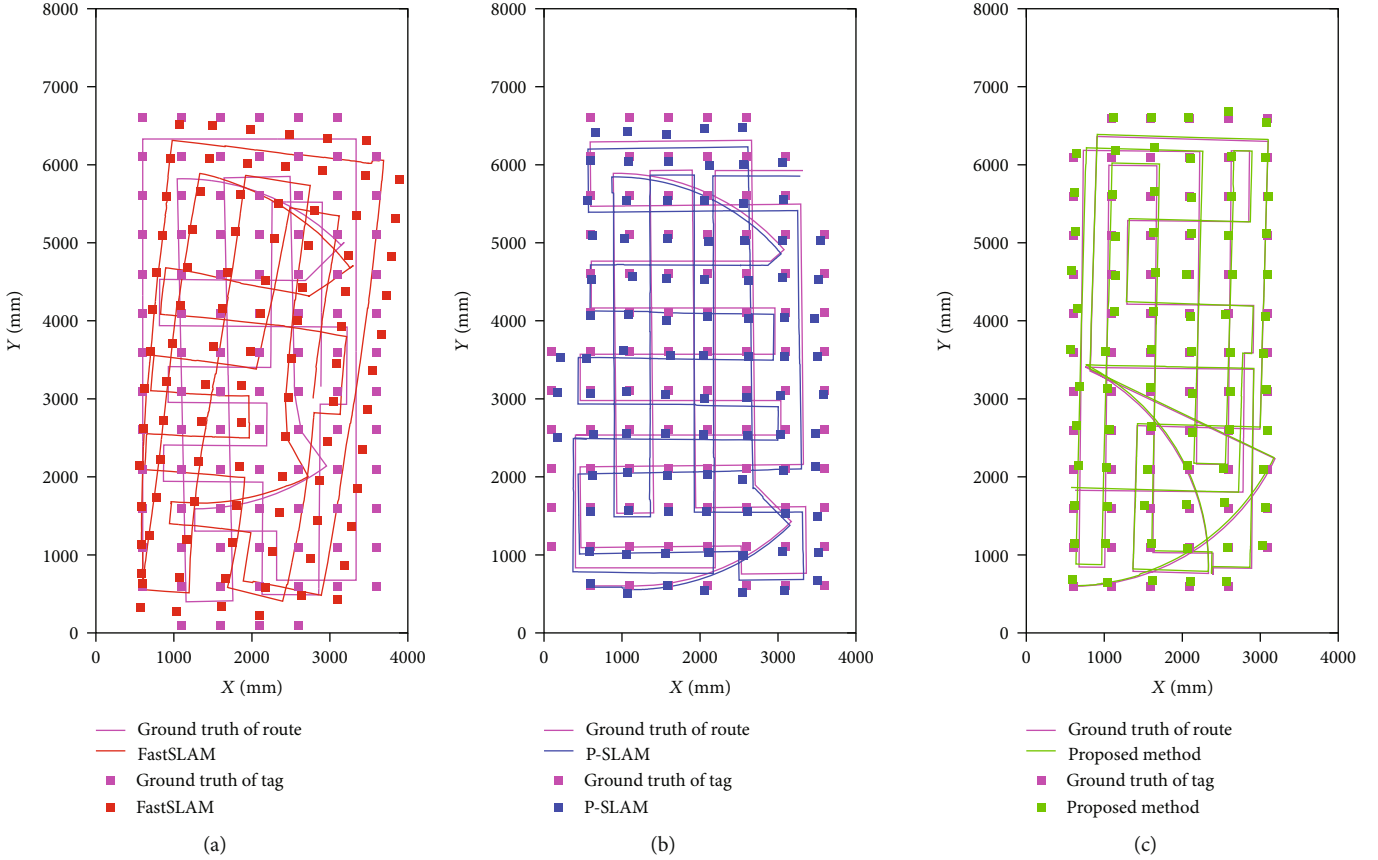


FIGURE 7: Results obtained by FastSLAM, P-SLAM, and the proposed method, using the RFID detection model on an unspecified trajectory. (a), (b), and (c), respectively, show the results obtained by FastSLAM, P-SLAM, and the proposed method.

Running on an unspecified trajectory makes the robot detect tags in more additional directions. The results were more accurate when the P-SLAM was evaluated on an unspecified trajectory than a predefined trajectory in [16]. Our proposed SLAM method also has this feature that the accuracy of tag location can be improved by detecting a tag in additional alternative directions. Because the particles are updated using a pseudorandom value when a tag is detected multiple times, the distribution of the tag particles cannot be narrowed to a point by detecting the detected tag in different directions. However, this also preserves the possibility of a correct estimation when errors occur and prevents the particles from converging to an unrecoverable and incorrect estimation.

We tested the proposed SLAM method by letting the robot move along an unspecified trajectory to verify this hypothesis. Figure 7 shows the results obtained by FastSLAM, P-SLAM, and the proposed SLAM method. The

results obtained by FastSLAM show a large deviation from the trajectory and the actual tag locations, as shown in Figure 7(a). Figure 7(b) shows a comparison between ground truth data and estimations generated by P-SLAM. Figure 7(c) shows comparisons between the ground truth data with the path of the robot and tag locations estimated by the proposed method on an unspecified trajectory. The estimations by our proposed method and P-SLAM were more accurate on an unspecified trajectory than the estimations on a predefined trajectory. However, the path of the robot and tag locations estimated by the proposed method achieved better overlaps than P-SLAM on the unspecified trajectory.

Table 5 summarizes the error data generated by FastSLAM, P-SLAM, and the proposed method, on an unspecified trajectory. FastSLAM generated larger errors relative to the other two methods. P-SLAM obtained better results on the unspecified trajectory than on the predefined

TABLE 5: Errors of the robot and tag localization generated by FastSLAM, P-SLAM, and the proposed SLAM method, using the RFID detection model on an unspecified trajectory.

Method	Robot location				Tag location		
	$x$ (mm)	$y$ (mm)	$\theta$ (rad)	$d$ (mm)	$x$ (mm)	$y$ (mm)	$d$ (mm)
FastSLAM	110.4	198.6	0.131	245.7	122.5	234.1	280.0
P-SLAM	61.0	25.3	0.007	66.7	67.5	38.5	82.3
Proposed method	21.0	15.1	0.010	29.1	31.9	32.9	50.4

trajectory, as also demonstrated in [16]. For our proposed method, the average position errors of the robot and tag localization were approximately 30 mm and 50 mm, respectively. The average orientation error of the robot was 0.010 rad. Comparing to P-SLAM, our proposed method obtained better performance on the unspecified trajectory. Furthermore, the robot self-localization and tag locations obtained by the proposed method on the unspecified trajectory were also better than those obtained on the predefined trajectory. This proves the validity of the hypothesis mentioned above. Although the particles for estimating the detected tag cannot be converted to a small range via the smoothing method, the accuracy and stability are improved.

#### 4.2. Experiment with the Range and Bearing Detection Model.

In the simulation, a general range and bearing sensor belonging to a Gaussian detection model was also utilized to evaluate the proposed method, P-SLAM, and FastSLAM. An illustration of the mobile robot with a range and bearing sensor is shown in Figure 8. The detection range was set to 500 mm, and the detection angle was set to 120 deg. The landmark perception was modeled with independent zero-mean Gaussian noise  $\varepsilon_r$  and  $\varepsilon_b$  on the range and bearing. The standard deviations  $\sigma_r$  and  $\sigma_b$  were set to 10 mm and 3 deg, respectively. The robot with the range and bearing sensor was operated on two types of predefined trajectories: with rotation and without rotation.

##### 4.2.1. Predefined Trajectory without Rotation Experiment.

The robot with the range and bearing sensor moved along five predefined trajectories without rotation to evaluate the proposed method. The robot also runs on each predefined trajectory three loops. The results of the path of the robot and tag locations generated by our proposed method and the other two SLAM methods on a predefined trajectory without rotation are shown in Figure 9. Figure 9(a) shows the path of the robot and tag locations estimated by FastSLAM. Although the results generated with the range and bearing sensor were better than those generated with the HF-band RFID sensor, deviations occurred during the movement. Both the route of the robot and tag positions estimated by FastSLAM have an offset to the upper left. Figure 9(b) shows that the tag positions estimated by P-SLAM overlap with the ground truth. However, the routes of the robot show unstable performance. In comparison, both the path of the robot and tag locations estimated by the proposed method overlap with the ground truth on the predefined trajectory, as Figure 9(c) shows.

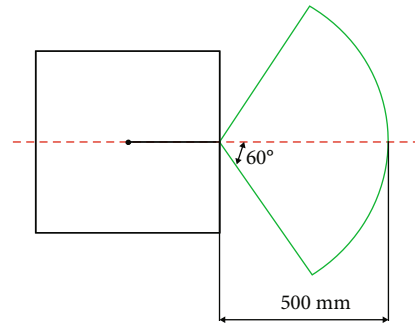


FIGURE 8: Robot with the range and bearing sensor.

Table 6 lists the errors of the robot self-localization and tag locations generated by FastSLAM, P-SLAM, and our proposed method. The errors represent the average errors on the five different trajectories. For our proposed method, the position error of the robot is approximately 113 mm and the orientation error is 0.016 rad. The position error of the tag locations by the proposed SLAM method is approximately 112 mm. Unlike with the RFID sensor, the results obtained by our proposed method on the predefined trajectory without rotation are similar to those obtained by P-SLAM. The robot ran on a predefined trajectory without rotation, which prevents the noise in the bearing from being modified effectively. Therefore, the particle smoother method for estimating landmarks does not show its superiority over the particle filter method. However, both these SLAM methods obtained better performance than FastSLAM.

##### 4.2.2. Predefined Trajectory with Rotation Experiment.

Figure 10 shows the performance obtained by our proposed method, P-SLAM, and FastSLAM using a range and bearing sensor on a predefined trajectory with rotation. The path of the robot and tag locations estimated by FastSLAM are shown in Figure 10(a). On the trajectory with rotation, the results obtained by FastSLAM using the range and bearing sensor were more accurate than those obtained using the HF-band RFID system. Figure 10(b) shows the estimations obtained by P-SLAM. Although some deviations appear, the estimations are more accurate than those obtained by FastSLAM. However, as Figure 10(c) shows, the proposed method exhibits the best performance.

Table 7 lists the average robot self-localization errors and tag location errors on the five predefined trajectories with rotation, as obtained by our proposed method, P-SLAM, and FastSLAM. The average position and orientation errors of the robot are approximately 97 mm and 0.012 rad,



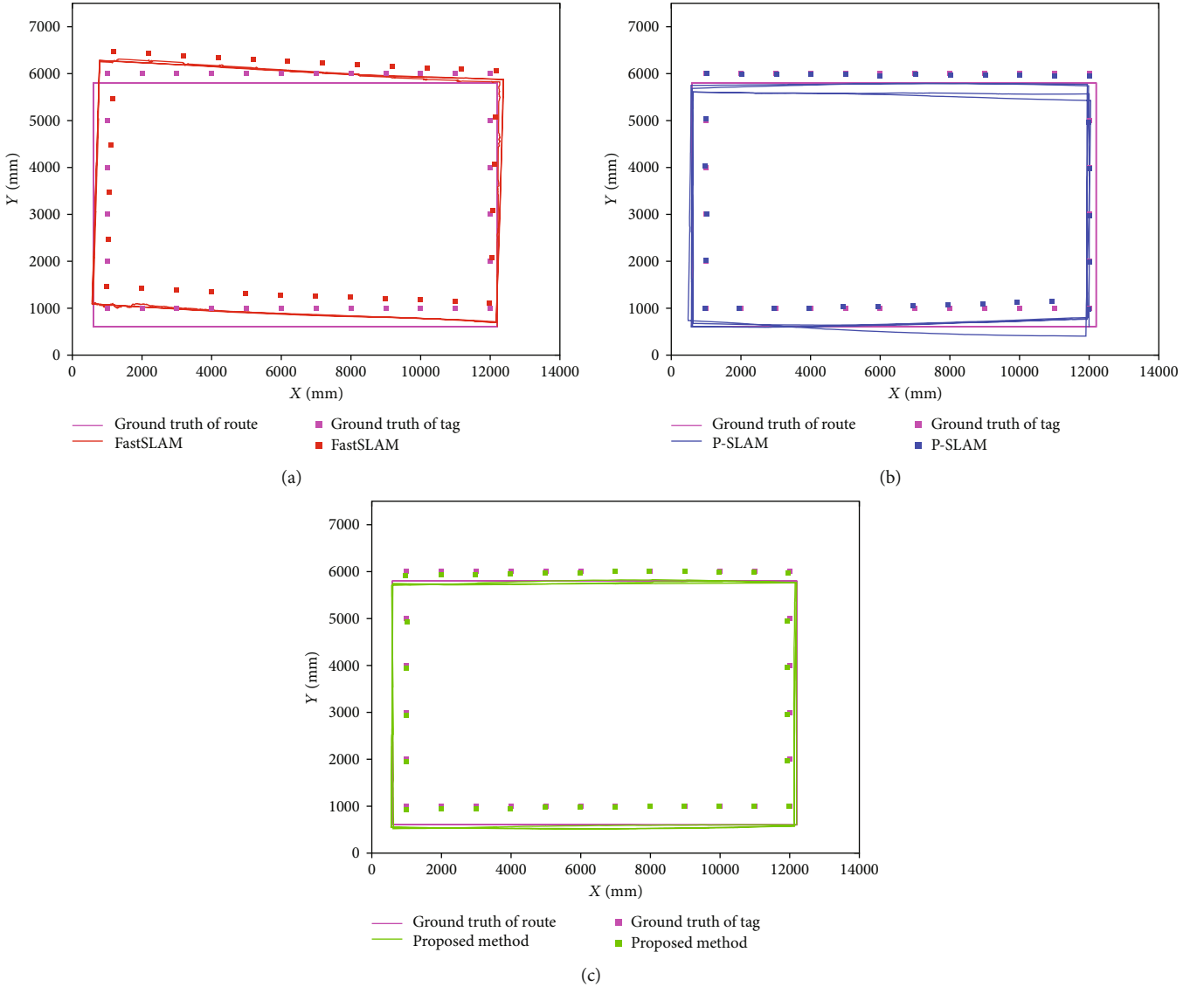


FIGURE 9: Results obtained by FastSLAM, P-SLAM, and the proposed method, using a range and bearing sensor on a predefined trajectory without rotation. (a), (b), and (c), respectively, show the results obtained by FastSLAM, P-SLAM, and the proposed method.

TABLE 6: Errors of the robot and tag localization generated by FastSLAM, P-SLAM, and the proposed SLAM method, using a range and bearing sensor on predefined trajectories without rotation.

Method	Robot location				Tag location		
	$x$ (mm)	$y$ (mm)	$\theta$ (rad)	$d$ (mm)	$x$ (mm)	$y$ (mm)	$d$ (mm)
FastSLAM	106.1	213.8	0.031	259.4	105.4	231.4	281.5
P-SLAM	42.2	90.8	0.013	108.4	40.8	52.6	70.9
Proposed method	55.4	85.2	0.016	113.2	53.1	86.3	111.5

respectively, when using our proposed SLAM method. The average position error of the tag locations is approximately 93 mm. On the predefined trajectory with rotation, our proposed method generated smaller errors than P-SLAM. This proves the hypothesis that the noise in the bearing can be

modified effectively by using the proposed method when the robot moves on the trajectory with rotation. The average distance error estimated by FastSLAM is approximately 270 mm, which is three times the average distance error generated by our proposed method.

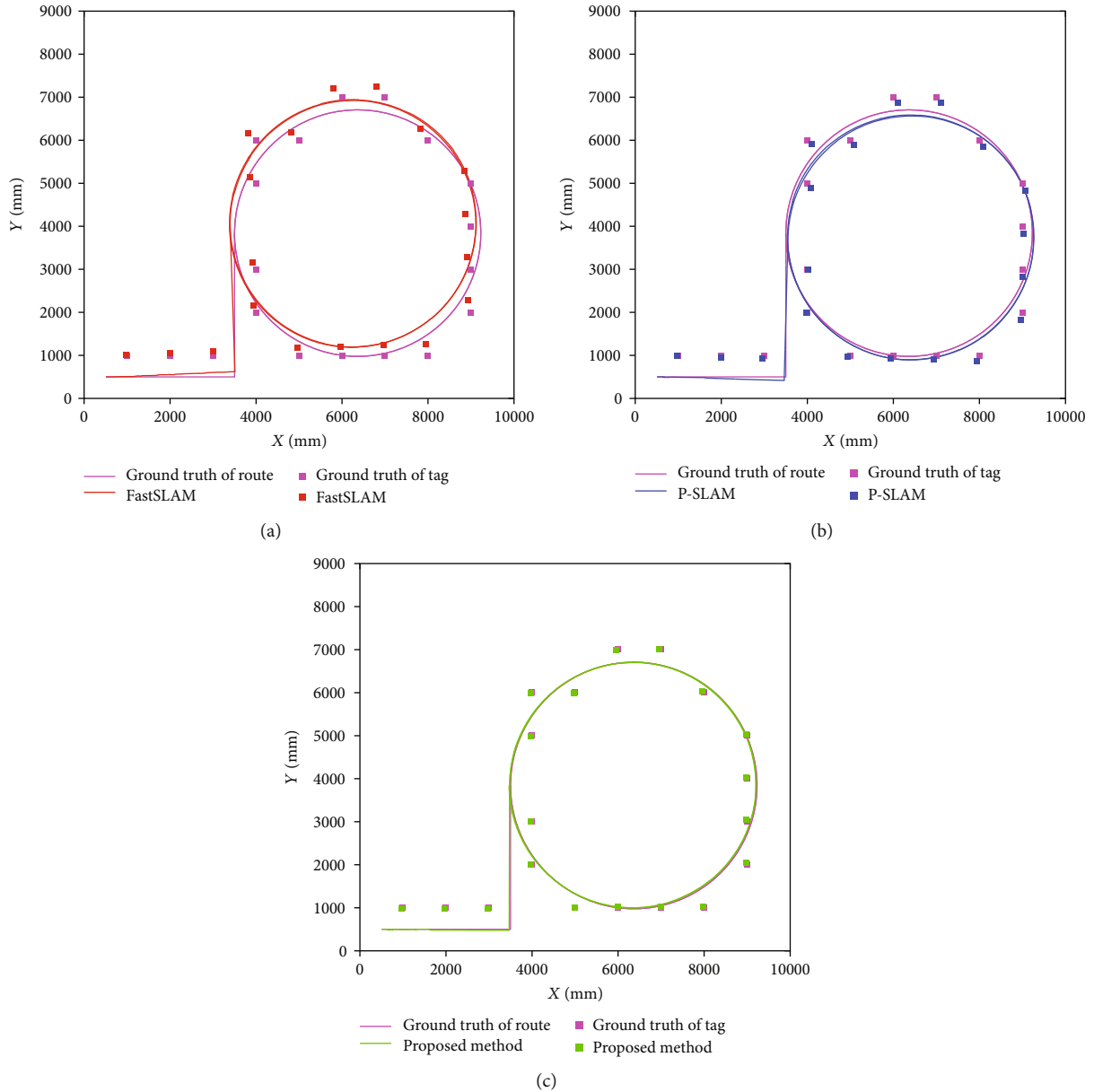


FIGURE 10: Results obtained by FastSLAM, P-SLAM, and the proposed method, using a range and bearing sensor on a predefined trajectory with rotation. (a), (b), and (c), respectively, show the results obtained by FastSLAM, P-SLAM, and the proposed method.

TABLE 7: Errors of the robot and tag localization generated by FastSLAM, P-SLAM, and the proposed SLAM method, using a range and bearing sensor on predefined trajectories with rotation.

Method	Robot location				Tag location		
	$x$ (mm)	$y$ (mm)	$\theta$ (rad)	$d$ (mm)	$x$ (mm)	$y$ (mm)	$d$ (mm)
FastSLAM	114.4	237.8	0.040	275.1	100.7	218.1	251.3
P-SLAM	45.2	121.6	0.020	137.1	42.6	112.9	128.2
Proposed method	21.5	90.9	0.012	96.6	19.8	86.0	92.6

According to the experiments, our proposed method obtained better results than the other two SLAM methods. The experiment results obtained by FastSLAM prove that it is unsuitable for the sensors with the non-Gaussian detection

model. Our proposed method and P-SLAM not only show better performance with the RFID system but also with the range and bearing sensor, which incorporates the Gaussian detection model. P-SLAM obtained an accurate estimation

according to the detection range and interval of the landmarks. However, when comparing the results obtained by the proposed method against those obtained by P-SLAM, it is clear that our proposed method provides improved accuracy by using the particle smoother method to estimate landmark positions, particularly when using the RFID system with large detection range.

## 5. Conclusions

A novel SLAM technique based on particle smoothers for landmark mapping and a particle filter for self-localization of a mobile robot are proposed in this paper. HF-band RFID tags are used as the landmarks spread on the floor. Multiple readers are installed on the bottom of the mobile robot to detect the tags that allow the robot to estimate its position and orientation. The SLAM method is utilized to reduce the labor and time cost of collecting the IDs and positions of RFID tags, which are needed in the self-localization of mobile robots. However, a detection model using the HF-band RFID system cannot be modeled with a Gaussian distribution, which makes the Kalman filter unsuitable. Although the particle filter can handle the non-Gaussian distribution of the landmark detection, the degeneracy problem becomes more serious over time when a particle filter is used to update a landmark position. Therefore, the proposed SLAM method utilizes independent particle smoothers to update the positions of landmarks and a particle filter to update the position and orientation of the mobile robot. The particle smoother method reduces particle degeneration, preserves the possibility of a correct estimation when errors occur, and prevents the particles from converging to an unrecoverable and incorrect estimation. The smoothed estimation is more suitable to the stationary landmarks. The particle smoother is able to improve the accuracy and stability of the estimation in SLAM tasks. The proposed method is evaluated through experiments with the RFID detection model and the range and bearing detection model. Furthermore, the proposed method is compared against FastSLAM and P-SLAM. The experimental results show the validity and superiority of the proposed SLAM method on both the RFID detection model and the range and bearing detection model.

The graph-based optimization method is widely used in the laser and visual SLAM. Considering the computational cost of the graph-based optimization method (that is linear in the number of observations) to the computational cost of filtering (that is cubic in the number of observations), the graph-based optimization method is the more efficient technique. However, the number of observations in our approach is much less than that in visual SLAM. Furthermore, majority of graph optimizers assume Gaussian noise in the constraints, and considering the non-Gaussian distribution of the HF-band RFID detection model, the particle filter with the nonparametric inference was preferred in this research. Several works have been proposed to cater for non-Gaussian noise, e.g., using robust cost functions [39], robust optimization methods [40], or explicitly handling non-Gaussian distributions [41]. The utilization of these optimization

methods to the HF-band RFID-based SLAM would be an interesting topic for our future work.

## Data Availability

The data used to support the findings of this study are available from the corresponding author on reasonable request.

## Conflicts of Interest

The authors declare no conflicts of interest.

## Acknowledgments

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