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Research Article

A Moving Object Indoor Tracking Model Based on Semiactive RFID

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Aimed at the weak anti-interference and low accuracy problem of moving object indoor tracking based RFID, a moving object indoor tracking model based on semiactive RFID is presented. This model acquires scene location information through RFID low frequency triggers preinstalled, which can enhance the anti-interference ability. This model adopts an improved particle filter algorithm, which can increase the diversity of the particles, overcome the particle impoverishment, and reduce the tracking error. Simulation results indicate that the model can achieve better tracking performances. Compared with standard particle filter, the improved algorithm performance is better in the capability of tracking accuracy and robust and is more suitable for indoor tracking application in the complicated environments.

1. Introduction

According to the difference in obtaining energy of the electronic tag, RFID technology can be divided into passive, active, and semiactive technologies. The passive electronic tag does not contain a power supply inside and utilizes beam power supply technology. Thomas F Bechteler et al. used passive tags to achieve 2D positioning of indoor targets with positioning errors within 20 cm [1]. Po Yang et al. achieved indoor positioning and tracking of targets in a passive RFID tag environment with an error of about 5 cm [2]. Passive RFID positioning generally uses signal arrival time, signal arrival time difference, and signal arrival angle for positioning, having the advantages of low price and high positioning accuracy. However, passive RFID positioning is not suitable for long-distance indoor positioning because the working distance is relatively close and the positioning accuracy is susceptible to obstacles. The active electronic tag has a power supply inside and an automatic answering function. The LANDMARC system [3] is an active RFID indoor positioning system proposed by Ni L M, etc., with a positioning accuracy of 50% probability of positioning error within 1 meter. The VIRE algorithm [4] is a positioning method improved by Zhao Yi-yang et al. based on the LANDMARC algorithm. By introducing a virtual reference tag, the positioning accuracy of VIRE is further improved. Active RFID positioning generally uses signal strength for positioning and has the characteristics of long positioning distance but has the problems of poor anti-interference and low positioning accuracy. Semiactive RFID technology utilizes low-frequency close-range activation of tags, high-frequency long-distance identification, and data communication and combines some of the characteristics of passive and active tags. At present, there are few researches on semiactive indoor positioning, but the semiactive RFID technology has the advantages of strong controllability and good anti-interference. The semiactive indoor positioning has a long distance, and the positioning accuracy is high, which has a great development potential.

Mathematically, moving target tracking is defined as the process that estimates the state of a moving target based on observations with noise. The state of a target is generally characterized by one or more of its information such as position, velocity, and acceleration. The real-time tracking problem of moving targets is solved by filtering the current state. The typical filtering algorithm has Bayesian filtering [5], Kalman filtering [6, 7], extended Kalman filtering [8], unscented Kalman filtering [9], and particle filtering [10]. For nonlinear systems with non-Gaussian noise, these methods

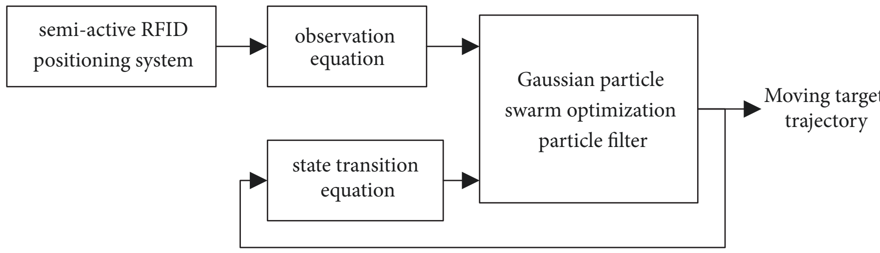


Figure 1: System model.

including Kalman filtering, extended Kalman filtering, and unscented Kalman filtering are difficult to obtain the estimated results that meet the requirements. Particle filtering is a filtering method that directly estimates the posterior probability density function sampling and becomes one of the most important solutions to the estimation problem in nonlinear non-Gaussian systems.

P Vorst et al. proposed particle filter algorithm to achieve indoor tracking of moving targets, but the standard particle filtering algorithm has problems such as particle degradation and particle sample depletion, which affects the tracking accuracy of moving targets [11]. Particle swarm optimization (PSO) is an optimization algorithm based on swarm intelligence theory. It is optimized by intelligent information generated by cooperation and competition among particles in the group. In [12], the authors give an improved particle filtering algorithm based on particle swarm optimization and apply the algorithm to target tracking, which can improve particle sample impoverishment. The selection of inertial coefficient, acceleration constant, and other parameters in the particle swarm optimization algorithm is closely related to the actual application and is generally determined by experience or experiment. Improper selection will directly affect the performances, and the optimization purpose cannot be achieved. The Gaussian particle swarm optimization algorithm [13] is an improved algorithm proposed by Krohling in 2004. In Gaussian particle swarm optimization, the Gaussian distribution is used to update the particle velocity and position information, and only one parameter of the number of particles needs to be determined. In this paper, the indoor target tracking system model based on semiactive RFID is studied. The indoor tracking model of moving target based on semiactive RFID and particle filter is given, and a particle filter based on Gaussian particle swarm optimization is designed to improve indoor tracking performance of moving targets.

2. The Proposed System Model

The indoor tracking of moving targets can be modeled as a nonlinear state estimation problem. The moving target state is estimated according to the moving equation and the observation equation of the moving target, and the filter is used to smooth the target state. The proposed model of the moving target indoor tracking system based on semiactive RFID technology is shown in Figure 1. It consists of a semiactive RFID positioning system, an observation equation, a state transition equation, and a Gaussian particle swarm optimization particle filter.

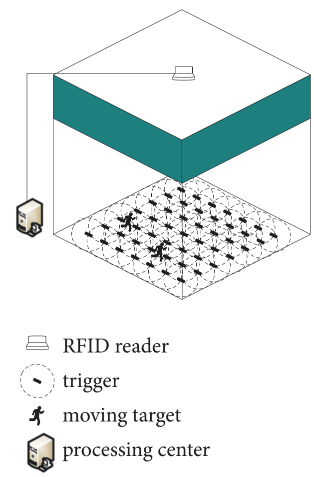


Figure 2: Positioning system based on semiactive RFID.

2.1. Semiactive RFID Positioning System. The semiactive RFID positioning system consists of an RFID reader, trigger, dual-band RFID card, moving target, and position processing center, as shown in Figure 2.

The card reader is positioned on the ceiling above the positioning area to automatically identify the RFID card information over long distances. The trigger transmits low-frequency signals in real time and is arranged under the floor according to a certain density according to the positioning accuracy, covering the target positioning area, as shown in Figure 3. The dual-band RFID card integrates two frequencies, low frequency and high frequency, which can be pasted to a moving target or carried by a moving target. The high frequency module of the RFID card is normally in a dormant state. When the RFID card enters the triggering area, the low-frequency module can receive the signal sent by the trigger in the sleep state of the RFID card and activate the high-frequency module, and the dual-frequency RFID card transmits high-frequency signal which contains the identification code and the trigger number information. If the card reader obtains the identification code of the RFID card, the trigger number, and the like, the information, are transmitted to the location processing center through the network port or the serial port, and the location processing

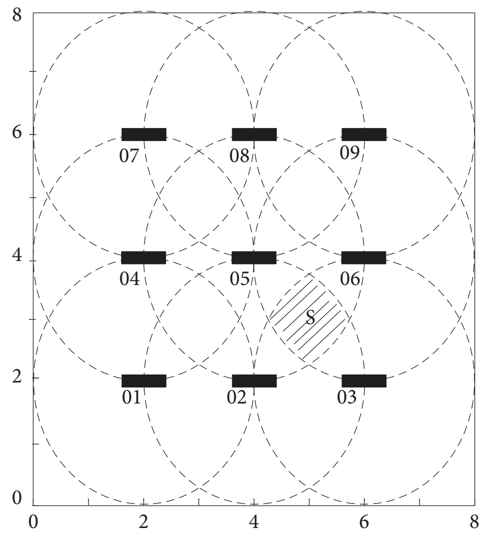


Figure 3: The deployment of triggers.

center calculates the location information of the mobile target.

The semiactive RFID positioning acquires the scene position information by presetting the RFID low-frequency trigger and uses the reader to locate the sensing result of the dual-frequency RFID tag in the positioning area. Assume that N triggers are evenly placed on the floor, which are presented with $TR = \{tr_i,\ i = 1, 2, \cdots, N\}$, and the corresponding coordinate positions are $\{(x_i, y_i),\ i = 1, 2, \cdots, N\}$. If the moving target is activated by M triggers at the k moment, which is presented with $RFID = \{rfid_k,\ k = 1, 2, \cdots, M\}$, and $rfid_k \in TR$, the corresponding coordinate positions of triggers are $\{(x_j, y_j),\ j = 1, 2, \cdots, M\}$. It can be considered that the moving target is in the common area of M triggers working area; the coordinate position can be estimated by

$$m_{RFID} = (x_{RFID}, y_{RFID}) = \left(\frac{1}{M}\sum_{j=1}^{M} x_j, \frac{1}{M}\sum_{j=1}^{M} y_j\right) \quad (1)$$

2.2. Observation Equation. The semiactive RFID positioning result is used as the input of the observation equation, but since the effective working area of the trigger is not a standard circular shape, there will be measurement errors in the boundary area. The observation equation can be expressed as

$$z_k = m_{RFID} + q_k \quad (2)$$

where z_k is observation value and q_k is observation noise.

2.3. State Transition Equation. The state transition process of the moving target in two-dimensional plane coordinates is shown in Figure 4.

Assume that the moving target reaches point A at the k moment, which is presented with $x(k) = (x_k, y_k, \theta_k)$, and (x_k, y_k) are two-dimensional coordinates; θ_k is phase angle. After Δk time interval, the moving target moves to point B,

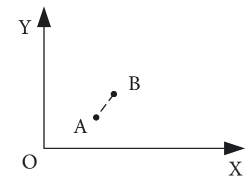


Figure 4: The state transition process of a moving object.

which is presented with $x(k+1) = (x_{k+1}, y_{k+1}, \theta_{k+1})$, where Δk is sampling interval. If Δk is smaller, the moving target can be regarded as uniform linear motion during Δk; the distance of movement Δd_k can be expressed as

$$\Delta d_k = \sqrt{(x_k - x_{k-1})^2 + (y_k - y_{k-1})^2} \quad (3)$$

The state transition equation can be expressed as

$$x(k+1) = \begin{bmatrix} x_k + \Delta d_k \cos(\theta_k) \\ y_k + \Delta d_k \sin(\theta_k) \\ \theta_k + \Delta\theta_k \end{bmatrix} + r_k \quad (4)$$

where r_k is process noise; $\Delta\theta_k$ is the change in phase angle after Δk time interval.

2.4. Gaussian Particle Swarm Optimization Particle Filter. Standard particle filters are prone to depletion in particle sampling during the importance sampling process. The Gaussian particle swarm optimization algorithm can be used to improve the performance of the standard particle filter. The Gaussian particle swarm optimization particle filter (GPSO-PF) is obtained by effectively combining the two algorithms. The flow chart is shown in Box 1. GPSO-PF makes the particles move toward the high likelihood region before the weight update, improve the utility of each particle, and alleviate the degradation of the particle weight.

3. Simulation Experiment and Evaluation

In order to measure the feasibility and effectiveness of the semiactive RFID based indoor target tracking system model and to evaluate its tracking performance, MATLAB simulation was used for analysis and comparison.

3.1. Simulation Scene and Parameter Settings. The simulation test is carried out by using MATLAB software. It is assumed that the simulation experiment is in an 8m∗8m hall. The card reader is deployed on the ceiling above the positioning area, and the RFID card information can be automatically recognized by long distance wireless. The trigger transmits low-frequency signals in real time and is laid on the floor. A total of 7∗7 triggers are deployed. Each trigger area is a circle with a radius of 1 meter, and the distance between the two triggers is 2 meters.

In Figure 5(a), the starting position of the moving target is A (2, 0.5), moving along a straight line to B (6, 4.5) with an angle of 45° to the x-axis. In Figure 5(b), the starting position

$\left[\left\{x_k^{(i)}, w_k^{(i)}\right\}_{i=1:N}, \widehat{x}_k\right] = GPSOPF\left[\left\{x_{k-1}^{(i)}, w_{k-1}^{(i)}\right\}_{i=1:N}, z_k\right]$

(1) Sequential importance sampling

For $i = 1 : \mathrm{N}$

$z_k = m_{RFID} + n_k$

$x_k^{(i)} \sim q\left(x_k^{(i)} \mid x_{k-1}^{(i)}, z_k\right)$

$$\widetilde{w}_k^{(i)} = \widetilde{w}_{k-1}^{(i)} \frac{p\left(z_k \mid x_k^{(i)}\right) p\left(x_k^{(i)} \mid x_{k-1}^{(i)}\right)}{q\left(x_k^{(i)} \mid x_{k-1}^{(i)}, z_k\right)}$$

End for

(2) Re-sampling

$$\widehat{N}_{eff} = \left(\sum_{i=1}^{N}\left(w_k^{(i)}\right)^2\right)^{-1}$$

If $\widehat{N}_{eff} \le N_{thr}$

$[\{x_k^{(i)}, w_k^{(i)}\}_{i=1}^{N}] = \mathrm{Re}\,sample[\{x_{k-1}^{(i)}, w_{k-1}^{(i)}\}_{i=1}^{N}]$

End If

(3) State estimation

$$w_k^{(i)} = \frac{\widetilde{w}_k^{(i)}}{\sum_{i=1}^{N}\widetilde{w}_k^{(i)}}$$

$$\widehat{x}_k = \sum_{i=1}^{N} x_k^{(i)} w_k^{(i)}$$

(4) Particle distribution optimization process

$\left[\left\{x_k^{(j)}, w_k^{(j)}\right\}_{j=1}^{N}\right] = GPSO\left[\left\{x_k^{(i)}, \widetilde{w}_k^{(i)}\right\}_{i=1}^{N}\right]$

①Initialization

$\left[\left\{px^{(i)}, pv^{(i)}, pfit^{(i)}, pbest^{(i)}, gbest^{(i)}\right\}_{i=1}^{N}\right] \sim \left[\left\{x_k^{(i)}, w_k^{(i)}\right\}_{i=1}^{N}\right]$

②Particle optimization

For $m = 1 : Gen$

$v_i^{m+1} = \mathrm{rand}(\cdot) \cdot \left(pBest_i^m - x_i^m\right) + \mathrm{rand}(\cdot) \cdot \left(gBest - x_i^m\right), \ i = 1, 2, \cdots, N$

$x_i^{m+1} = x_i^m + v_i^m, \ i = 1, 2, \cdots, N$

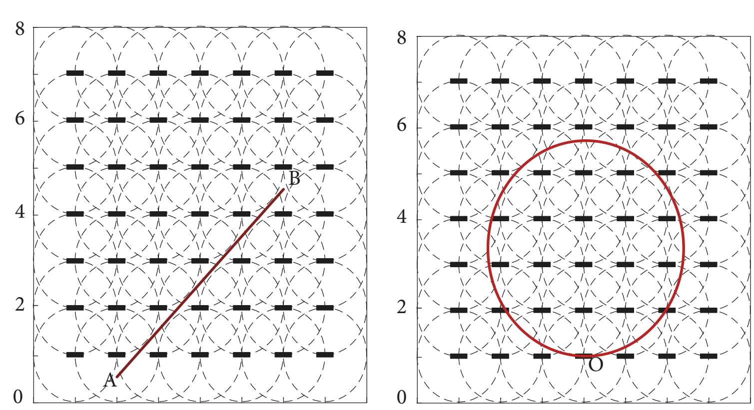
$\left[\left\{px^{(mi)}, pv^{(mi)}, pfit^{(mi)}, pbest^{(mi)}, gbest^{(mi)}\right\}_{i=1}^{N}\right]$

End for

③ Particle assignment

$\left[\left\{x_k^{(j)}, \widetilde{w}_k^{(j)}\right\}_{j=1}^{N}\right] \sim \left[\left\{px^{(mi)}, pfit^{(mi)}\right\}_{i=1}^{N}\right]$

Box 1: Flow chart of GPSO-PF.

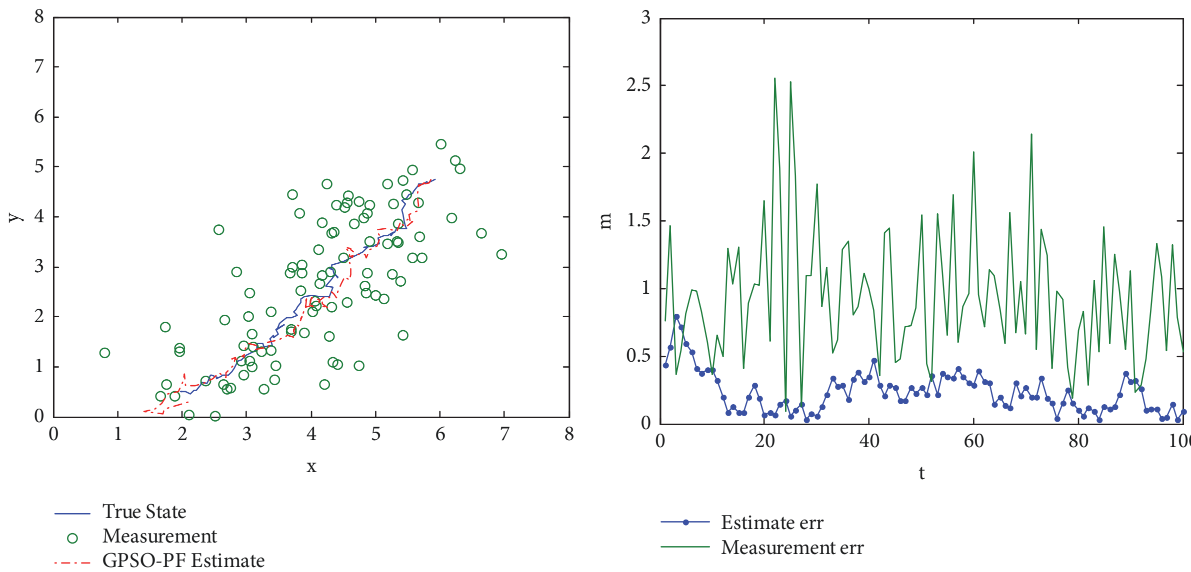


(a) Rectilinear motion (b) Circling motion

Figure 5: Simulation scenario.

Table 1: Simulation parameter setting.

Simulation parameter	Description	Setting value
N	Number of particles	50
R	Process noise variance	0.0025
Q	Observed noise variance	0.5
M	Number of iterations	5
L	Number of simulation steps	100



(a) Moving trajectory

(b) Estimate error

Figure 6: Moving trajectory and error of rectilinear motion.

of the moving target is O (4, 1), moving counterclockwise along the circumference of a radius of 2.5 meters.

Both process noise and observed noise are Gaussian white noise, and the simulation parameters are set as shown in Table 1.

3.2. Performance Analysis. Suppose that the actual coordinates and estimated coordinates of an object are (x_0, y_0) and (x'_0, y'_0). To measure algorithm performance, estimation error e is defined as

$$e = \sqrt{(x'_0 - x_0)^2 + (y'_0 - y_0)^2} \tag{5}$$

The simulation running track and estimation error of linear motion are shown in Figure 6. The simulation running track and estimation error of circular motion are shown in Figure 7.

It can be seen from Figures 6 and 7 that the moving target is linear motion, the maximum error is 2.5545m, the average error is 0.9414m, and the maximum error is 0.7969m after filtering by GPSO-PF algorithm, and the average estimation error is 0.2340m. While the moving target is circular motion, the maximum error is 2.1745m and the average error is 0.8517m. The maximum error is 0.8166m and the average estimation error is 0.2345m after filtering by GPSO-PF algorithm. For semiactive technology for target positioning and tracking, whether it is linear motion or circular motion, even though the measurement error is large, the ideal tracking effect can be achieved by using GPSO-PF algorithm, which indicates that the proposed model is feasible and effective.

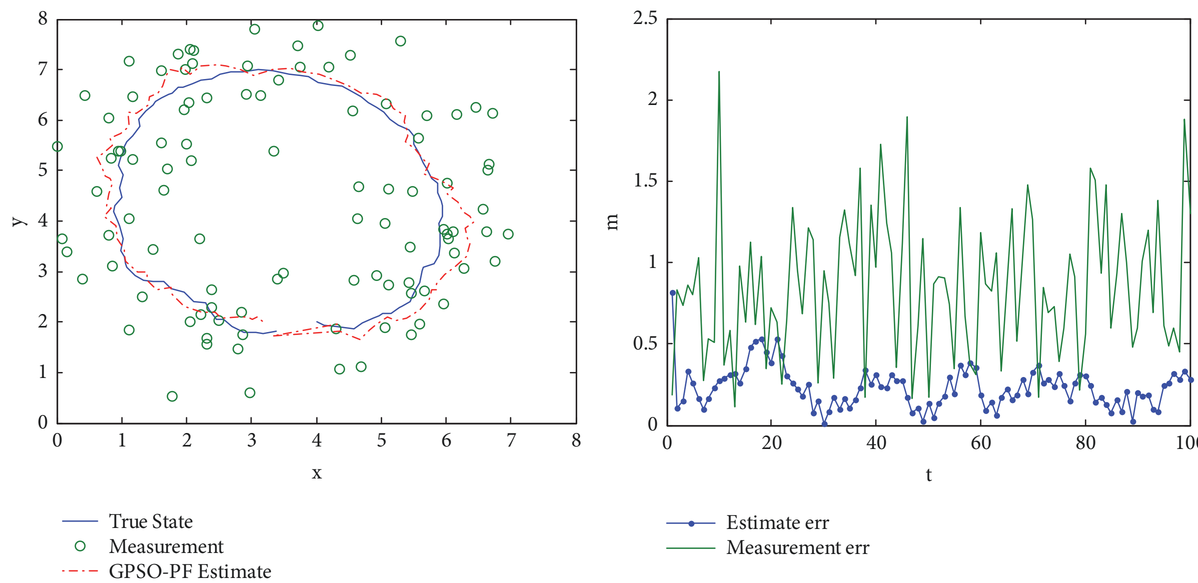
In order to better explain the performance of the GPSO-PF algorithm, the performance comparison with the standard particle filter PF is performed, and the simulation scene and configuration parameters remain unchanged. Select Root Mean Square Error (RMSE) as an indicator to evaluate the performance of the algorithm; RMSE is defined as

$$RMSE = \sqrt{\frac{1}{T} \cdot \sum_{k=1}^{T} (x_k - \hat{x}_k)^2} \tag{6}$$

The average of the RMSE is used to represent the filtering accuracy of the algorithm, and the variance of the RMSE is used to measure the stability of the algorithm. For each of the two algorithms, linear motion and circular motion were performed for 1000 Monte Carlo experiments, and the RMSE value curve is shown in Figure 8.

Calculate the mean and variance of RMSE, as shown in Table 2.

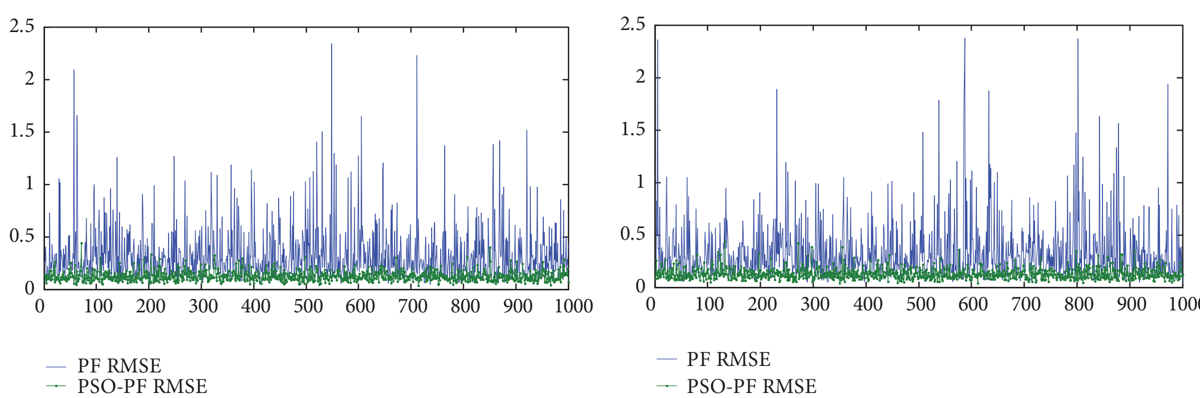
It can be seen from Table 1 that, compared with the PF algorithm, the RMSE mean value of the GPSO-PF algorithm



(a) Moving trajectory

(b) Estimate error

Figure 7: Moving trajectory and error of circling motion.



(a) Rectilinear motion

(b) Circling motion

Figure 8: RMSE of Monte Carlo simulation.

applied to the moving target for linear motion is increased by 61.8%, and the RMSE mean value of the GPSO-PF algorithm applied to the circular motion of the moving target is increased by 61.3%. Tracking filtering accuracy is greatly improved. The RMSE variance of GPSO-PF algorithm applied to moving targets for linear motion is 3.25% of PF algorithm. The RMSE variance of GPSO-PF algorithm applied to circular motion of moving targets is 3.37% of PF algorithm, and the stability of indoor tracking is greatly improved.

Simulation results indicate that the GPSO-PF algorithm has better performances than the standard particle filter in the capability of tracking accuracy and robust; the reason is that the Gaussian particle swarm optimization algorithm is introduced into the standard particle filter. To the problem of particle impoverishment, GPSO-PF algorithm incorporates the newest observations into sampling process and also optimizes the particles. Through particles distribution optimization process, the particles are moved toward regions where they have larger values of posterior density function. As a result, the diversity of the particles increases, the particle impoverishment is solved, and the tracking error is reduced dramatically.

The proposed model of this paper is compared with literature [1], literature [3], and literature [11] schemes in four aspects: RFID technology, positioning error, support for moving targets, and filtering algorithm, as shown in Table 3.

It can be seen from Table 2 that the general indoor positioning algorithm is not suitable for tracking of moving targets, and the indoor tracking requires filtering algorithm. The filtering algorithm of this model adopts GPSO-PF. The passive RFID positioning error is small, and the active RFID positioning error is large. The positioning error of this model is only 0.23m, which can achieve higher positioning accuracy.

Table 2: Mean value and variance of two algorithms.

Filtering algorithm	Rectilinear motion		Circling motion	
	RMSE mean	RMSE variance	RMSE mean	RMSE variance
PF	0.3300m	0.0708	0.3373m	0.0801
Proposed algorithm	0.1262m	0.0023	0.1304m	0.0027

Table 3: Performance comparison of four schemes.

Scheme	[1]	[3]	[11]	Proposed model
RFID technology	Passive	Active	Passive UHF	Semiactive
Positioning error	20cm	1m	0.5m	0.23m
Support for moving targets	No	No	Yes	Yes
Filtering algorithm	-	-	PF	GPSO-PF

4. Conclusions

In view of the shortcomings of current passive RFID technology and active RFID technology in indoor positioning in terms of distance and positioning accuracy, a semiactive RFID based indoor target tracking system model is proposed, which can achieve higher positioning and tracking accuracy. It can meet the needs of indoor location tracking in complex environments and has a good application prospect. The next research focus is that, due to the limitations of experimental conditions, the experimental data is obtained through simulation and is not verified in the real environment. The work that the proposed algorithm is tested and applied in the real environment will be done.

Data Availability

The experiment data used to support the findings of this study were supplied by Hongshan Kong under license and so cannot be made freely available. Requests for access to these data should be made to m13643861930@163.com.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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