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Research Article
An Improved Particle Filter Based on Firefly Algorithm used for Indoor Localization

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Abstract

Background and Objective: Traditional particle filter has long convergence time and it easily falls into local solution, which can results in the low precision of indoor localization. **Materials and Methods:** So, this study proposes an improved particle filter based on firefly algorithm to improve the positioning accuracy. The processes are divided into three steps. First, it introduces dynamic adaptive inertia weight into firefly algorithm to update the position of firefly. Second, the improved firefly algorithm is used to improve the sampling process of particle filter. It defines a new fitness function for particle filter. That makes the particles approach high likelihood area before weight updating and improves the re-sampling strategy. At last, it applies this new method into indoor localization. That is the first proposed scheme to improve particle filter currently. **Results:** Experiments show that new method improves the positioning accuracy and convergence speed. What's more, the accuracy of improved particle filter algorithm is better than traditional particle filter algorithm. Also, it makes comparison to other filter methods to demonstrate the effectiveness of new method. **Conclusion:** Particle filter based on firefly algorithm is an effective method, which can effectively improve the accuracy of localization.

Key words: Particle filter, indoor localization, firefly algorithm, dynamic adaptive inertia weight, sampling process

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INTRODUCTION

Generally, User-friendly interface[1] needs to adhere the design of people-oriented concept. It should take user's characteristics and requirements into consideration. UI[2,3] effectively reduces the user's cognitive burden and improves the usability of the user's interface and the efficiency of completing task. Positioning technology is a typical application, it has been widely used in military[4,5], science and people's life. Indoor positioning technology[6] as continuation of positioning technology in indoor environment makes up for the deficiency of the traditional positioning technology, it has a good application prospect. But indoor positioning technology has some disadvantages: (1) Due to the cover of the wall, GPS signal is very weak, (2) Many obstacles affect signal receiving such as sensor positioning equipment, sound and light. Therefore, particle filter is used for solving the above question in this study.

General particle filter adopts prior probability density distribution sampling to replace posterior probability density distribution sampling. It ignores the correction function of observation information resulting in the degradation of particle set. So, there are many improved methods for particle filter. Zhou *et al.*[7] proposed an improved Unscented Particle Filter (UPF) algorithm based on the analysis of Particle Filter (PF) by utilizing Unscented Kalman Filter (UKF) to obtain an importance density function. This algorithm clustered the sensor network nodes through dynamic organization. Moreover, the single target moving uniformly and linearly in the network was tracked by applying the UPF into the target tracking of Wireless Sensor Network (WSN). Walia and Kapoor[8] utilized cuckoo algorithm to improve particle filter which made sampling distribution move toward to the area of higher posterior probability. This method was very effective, but parameters of cuckoo algorithm are very complex, it was difficult to realize. So, this study proposes an improved particle filter in this study for indoor localization. The improved firefly algorithm is used in sampling process of particle filter. It improves the re-sampling strategy of particle filter. Finally, it makes experience to demonstrate the effective of our method. The following is the structure of this study.

MATERIALS AND METHODS

Particle filter and firefly algorithm

Particle filter: Particle filter[9-11] is a kind of statistics filter method based on Monte-Carlo sampling and recursive Bayesian estimation. It uses the weighted particles to approximately express the probability distribution. The posterior probability density distribution of the target state function can be discretely weighted as:

$$\hat{p}(x_{0:k} \mid y_{1:k}) \approx \sum_{i=1}^{N} w_k^i \delta(x_{0:k} - x_{0:k}^i) \tag{1}$$

Assuming that particles set are obtained by importance density function $q(x_k^i \mid x_{k-1}^i,\ y_k)$, so the weight is:

$$w_k^i \propto w_{k-1}^i \frac{p(y_k \mid x_k^i)p(x_k^i \mid x_{k-1}^i)}{q(x_k^i \mid x_{k-1}^i, y_k)} \tag{2}$$

Then the weight can be normalized as:

$$w_k^i = \frac{w_k^i}{\sum_{i=1}^{N} w_k^i} \tag{3}$$

Based on law of large numbers, when $N \to \infty$, Eq. 1 is closely to the posterior probability density $p(x_k|y_{1:k})$. In Eq. 2, $q(x_k^i \mid x_{k-1}^i,\ y_k)$ is used to replace the posterior probability density and executes sampling process. But in fact, it is difficult to do sampling directly from posterior probability density. Generally, it selects prior probability density function as importance density function, but general particle filter adopts this probability density function, it will cause poor particle problem. When observation value is accurate or likelihood function is at the end of the prior probability density, the overlapping portion between likelihood probability and prior probability is little. After updating weight, the weight of most particles becomes very small, which makes diversity of particles decrease.

Firefly algorithm: Firefly algorithm[12-14] can be defined that the search and optimization processes are simulated as the attracting and moving processes of firefly individual. Move direction of firefly individual is controlled by the different brightness. And moving distance correlates with attractiveness.

Relative brightness between firefly i and firefly j is:

$$I = I_0 \times e^{-\gamma r_{ij}} \tag{4}$$

where, I_0 is the biggest lightness related to function value and γ is light intensity absorption coefficient, which will recede with the increase of distance.

Attraction between firefly i and firefly j is:

$$\beta_{ij} = \beta_0 \times e^{-\gamma r_{ij}^2} \tag{5}$$

where, β_0 is the biggest attraction.

The position update equation of firefly i moving to firefly j is:

$$X_j(t+1) = X_j(t)+\beta_{ij}(X_i(t)-X_j(t))+\alpha\varepsilon \tag{6}$$

where, X_i and X_j are the position of firefly i and firefly j, respectively. The $\alpha\varepsilon$ is random disturbing term avoiding it falling into local solution.

In standard firefly algorithm, the brightness among fireflies is different, so they can attract each other, the distance between them will decrease, search ability will drop too. Firefly will falls into local solution. Although, $\alpha\varepsilon$ can remit this question, it needs lots of iterations to achieve precision, this will affect the optimization effect.

Improved particle filter based on firefly algorithm

Improved firefly algorithm: Aims to solve the above problem and improve the search ability of firefly, it designs a dynamic adaptive inertia weight for firefly algorithm. New position updating equation is:

$$X_j(t+1) = w(t)\ X_j(t)+\beta_{ij}(X_i(t)-X_j(t))+\alpha\varepsilon \tag{7}$$

$$w(t) = e^{-\frac{\lambda(t)}{\lambda(t-1)}} \tag{8}$$

$$\lambda(t) = \frac{1}{m}\sum_{i=1}^{m}(f(X_i(t)) - f(X_{best}(t)))^2 \tag{9}$$

where, w(t) is the t-th inertia weight, $f(X_i(t))$ is the target function value of t-th firefly in t-th iteration, $f(X_{best}(t))$ is the target function value of the optimal firefly at t-th position updating. In Eq. 8, when $t = 1$, $\lambda(0) = 0.9$. Using this computing method can make weight more smooth. When it updates function value, the $\lambda(t)$ will change. The inertia weight will dynamic change with function value. If $\lambda(t)$ decreases rapidly, w(t) will become bigger, so then it will enhance the global search ability. Therefore, it adds adaptive inertia weight for firefly algorithm, which can improve the search ability of firefly algorithm.

Improved firefly algorithm for particle filter: From the above analysis of firefly algorithm and particle filter, they have some similarities. First, particle filter approaches to system true posterior probability density by updating particle weight and position. Firefly algorithm searches the global optimal value by updating brightness and position of firefly. Second, the biggest weight in particle filter is the system state and the biggest fitness value of firefly individual is the optimal value in firefly algorithm. So, it can use improved firefly algorithm to perfect particle filter.

It introduces the latest observation value into sampling process of particle filter and define the new fitness function as follows:

$$y_k = e^{-\frac{1}{2R_k}(y_{new} - y_{pre})^2} \tag{10}$$

where, R_k is observation noise variance, y_{new} is latest observation value and y_{pre} is prediction observation value. Firefly algorithm computes fitness value to determine the brightness of each firefly. Firefly has a strong brightness with a bigger fitness value. So, it has strong attraction for the firefly with a smaller fitness value. In addition, it gets the new brightness of firefly by position updating equation. Through iterations, all the individuals approach to the position with brightest firefly. In fact, the particles approach to the high likelihood area. When the optimal value of individual meets the initial setting value, the firefly algorithm will stop. Then it calculates the weight of new particle $w_k^{i'}$. The $w_k^{i'}$ is normalized as:

$$w_k^i = \frac{w_k^{i'}}{\sum_{i=1}^{N} w_k^{i'}} \tag{11}$$

State estimation can be expressed as:

$$\hat{x}_k = \sum_{i=1}^{N} w_k^i x_k^i \tag{12}$$

To solve particle degeneration, it needs to execute re-sampling process for particles. Re-sampling process mainly selects and copies the particles with bigger weight. But it can result in reducing the particle diversity. So, it proposes a new re-sampling scheme.

New re-sampling strategy: Re-sampling process of traditional particle filter is based on the weight of each particle. The particle with bigger weight will be used for next iteration and can be duplicated many times. The particle with smaller weight will be rejected, which reduces the particle diversity and greatly influences the performance of algorithm. Therefore, it proposes a neighborhood re-sampling method based on particle with bigger weight.

Firstly, it computes the weight of each particle. Then the copied number n of each particle can be calculated as:

$$n = w_k^i / \frac{1}{N} \tag{13}$$

If n<1, let n = 0, the particles will be removed. If n>1, particle not only copies itself, but samples n-1 particles as new particles according to Gaussian distribution in neighborhood. All the weight is set as 1/N.

Through the above re-sampling method, it offsets the disadvantage of traditional particle filter. The particle obtained by new re-sampling method can keep the diversity of particle set. New re-sampling scheme is simple and efficient, its computational efficiency is higher.

Detailed processes of improved particle filter:

Step 1: Getting observation value, defining fitness function

Step 2: Initializing. It selects N particles $(x_0^i, i = 1, 2 \ldots N)$ from importance probability density function as initial sample and uses transfer prior probability as importance probability density

$$x_k^i \sim q(x_k^i \mid x_{k-1}^i, y_k) = p(x_k^i \mid x_{k-1}^i) \tag{14}$$

Step 3: Computing importance weight:

$$\begin{aligned} w_k^i &= w_{k-1}^i p(y_k \mid x_{k-1}^i) = w_{k-1}^i \frac{p(y_k \mid x_k^i) p(x_k^i \mid x_{k-1}^i)}{q(x_k^i \mid x_{k-1}^i, y_k)} \\ &= w_{k-1}^i e^{-\frac{1}{2R_k}(y_k - y_{k|k-1})^2} \end{aligned} \tag{15}$$

Step 4: According to firefly algorithm, fitness value is calculated by Eq. 10 as the biggest brightness I_0 of each firefly. The relative brightness and attraction are computed by Eq. 4 and 5. Relative brightness determines the moving direction of firefly. Firefly with bigger brightness attracts firefly with smaller brightness. It will continually update the position of firefly according to adaptive inertia weight position updating formula. Meanwhile, the brightness is updated too. When the brightness satisfies the threshold value, algorithm will stop

Step 5: Calculating the optimized importance weight and conducting normalization as Eq. 11

Step 6: Judging whether $N_e = 1 / \sum_{i=1}^{N} (w_k^i)^2 < N_{th}$, if $N_e < N_{th}$, then it does step 7. Otherwise, it returns to step 8

Step 7: Conducting re-sampling process

Step 8: Output: As given in Eq. 12

Step 9: Judging whether the algorithm meets stop condition. If YES. Then it stops. Otherwise, it returns to step 2

RESULTS AND DISCUSSION

It makes experiments under MATLAB platform. In order to verify effectiveness of our new algorithm, it selects the representative non-static growth model. System model and measurement model are as follows:

$$x_t = 0.5x_{t-1} + 25x_{t-1} / (1 + x_{t-1}^2) + 8\cos[1.2(t-1)] + w_t \tag{16}$$

$$y_t = x_t^2 / 20 + v_t \tag{17}$$

where, w_t and v_t are zero mean Gaussian noise. The characteristics of the system are highly nonlinear, likelihood function shows bi-modal feature, which makes traditional filter method difficult to solve problem. It also makes a comparison to standard Particle Filter (PF)[15], extended Kalman particle filter (EPF)[16], Unscented Particle Filter (UPF)[17] with our particle filter of improved firefly algorithm (IFAPF). Systemnoise $w_t \sim N(0, Q)$, measurement noise $v_t \sim N(0, R)$. Threshold of re-sampling is N_{th} = 0.4 N. Iteration number is 50. Initial value is zero. Evaluation indicator for filter adopts Root-Mean-Square Error (RMSE). The RMSE can be calculated as follows:

$$RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (x_n - \hat{x}_n)^2} \tag{18}$$

Also, it sets Q = 10, R = 1, N = 100. It conducts simulation experiment using different algorithms and gets the estimation value as Fig. 1.

Table 1 is the RMSE and required time. From Fig. 1, particle filter with improved firefly algorithm has the highest precision. Table 1 presents that RMSE of new algorithm is the smallest reduced by approximately 56% compared to PF. It reduced nearly 51 and 6% compared to EPF and UPF respectively. In addition, the new algorithm needs less convergence time.

The following is experiment for moving object localization in indoor environment. It makes comparison to PF, EPF, UPF and our IFAPF to verify effectiveness of our new method.

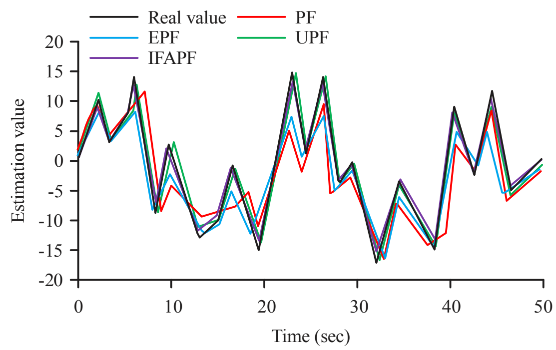

Fig. 1: Estimation value with different algorithms

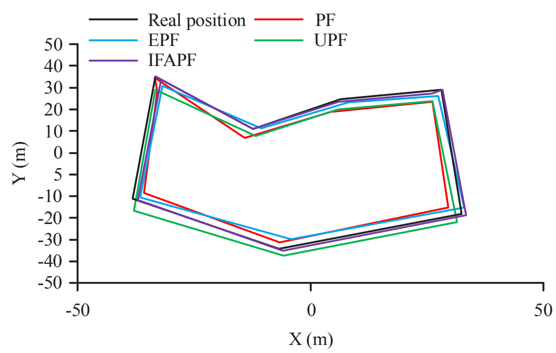

Fig. 2: Position with different algorithms

Table 1: RMSE and required time

Algorithm	RMSE (m)	Time (sec)
PF	4.4323	0.3289
EPF	3.9484	1.3822
UPF	2.0374	2.2521
IFAPF	1.8907	1.2173

Table 2: Localization time with different algorithms under different number of particles

	Algorithm			
No. of particle	PF	EPF	UPF	IFAPF
10	12.1022	29.8123	27.6492	16.5633
30	31.5178	48.6519	46.8317	43.9208
50	47.5163	73.5587	69.5372	53.1235

Experiment zone is 10×10 m indoor environment. Parameter is that speed of moving object is v = 2 m sec^{-1}, the biggest turning angle is 30°C, the biggest turning angle is 20°C sec^{-1}. Time interval is t = 0.5 sec. Figure 2 is the result of position with different algorithms.

From Fig. 2, PF has the worst localization result, in that it lacks observation correction function and has continuous error. The EPF has a better result than PF due to the importance density function and correction function of observation. But it results in poor particles problem because of re-sampling in EPF. Therefore, the position error is bigger. But localization result is the optimal based on IFAPF, because the new algorithm perfects particle filter and firefly algorithm. Improved re-sampling process and correction function of observation can improve the position estimation precision.

Table 2 shows the localization time with different algorithms under different number of particles. With the increase of particle number, localization time increases too. EPF needs the longest time among the four algorithms, because it makes linearization for nonlinear system and computes Jacobian matrix. This new method adopts improved firefly algorithm to make particles move toward to high likehood area. It adds adaptive weight avoiding falling into local solution. In conclusion, the new method has the optimal localization.

At present, indoor localization is a hot issue. Many researchers have done studies for it. For example, Kim *et al.*[18] used incremental method to update Gaussian mixture model and introduced new weight calculation method, which made the robustness of algorithm better. Liu and Yin[19] used improved adaptive acceleration factor and improved adaptive inertia weight to improve particle filter. Liu *et al.*[20] used variational Bayesian method to approximatively solve state joint probability density and measurement noise covariance of each measurement producer. Then it could obtain its recursive form to estimate measurement producer and adopted clustering method to get the state of extended target for the state of measurement producer. Liu and Yin[19] proposed an improved square root unscented kalman filter according to square root unscented Kalman filter and backward smoothing algorithm. This new scheme adopted equilateral triangle decomposition. He used square root of error covariance to replace covariance and executed recursive operation which could improve the stability and operation efficiency of algorithm. However, this study proposes the new method which greatly improves the accuracy of indoor localization. Comparing the simulation results with the theoretical analysis, this new algorithm can effectively short the convergence time and improve the localization accuracy in indoor environment. There are three main findings of this study especially to highlight the new findings:

- It uses a dynamic adaptive inertia weight to improve firefly algorithm
- It introduces observation value into particle sampling distribution to improve particle filter re-sampling process
- It improves the particle filter based on firefly algorithm

CONCLUSION

This study proposes an improved firefly algorithm used for particle filter in this study. It mainly improves the filter re-sampling process and introduces observation value into particle sampling distribution to make particle move toward to high likehood before updating weight. In addition, it uses the correction function of new observation value. New re-sampling process makes particle more diversity, which greatly improves the accuracy of localization. In the future, it will further improve this method and study more advanced particle filter methods to apply them into practical engineering applications.

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