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AN OPTIMIZED PARTICLE FILTER METHOD BASED ON IMPROVED GRAVITATIONAL FIELD ALGORITHM

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Abstract

Aiming at the problem of particle filter weight degradation and loss of diversity resulting in poor filter accuracy, an improved algorithm based on improved gravitational field optimization particle filter (Improved-GFA-PF, I-GFA-PF) was proposed. The resampling process of the particle filter algorithm is optimized by improving the gravitational field, namely using the gravitational field algorithm to optimize the particle set to be concentrated in the high-likelihood area to solve the weight degradation. To ensure particle diversity and filtering accuracy, the evaluation criteria of moving weight and rotation rejection factor were reset on the basis of the original algorithm, so as to increase the particles diversity and improve the filtering accuracy. The simulation results show that the filtering accuracy of the proposed I-GFA-PF is about 12% higher than that of the GFA-PF.

Keywords: particle filter, weight degradation, particle diversity, gravitational field algorithm, global optimal value.

1 INTRODUCTION

Particle filter (PF) [1] is an approximate Bayesian filtering algorithm based on Monte Carlo thought. Because it does not require the known noise model of the system, it is widely applied to nonlinear and non-Gaussian systems. The core idea of PF is to approximate the posterior probability density function of the system through a set of randomly distributed particles. At present, particle filter is widely used in robot positioning mapping[2], target tracking[3], fault detection and other fields[4]。

However, particle filtering still has problems in practical applications. Although the problem of particle weight degradation is solved by resampling strategy, it also causes the loss of particle diversity. In order to solve the above problems, scholars have proposed different improvement strategies, and with the in-depth study of the intelligent swarm algorithm, improving the particle filter through intelligent swarm algorithm has become a hot research topic[5-8]， Zhu Zhenshu et al.[9] proposed a particle filter algorithm combined with krill swarm optimization, which optimizes particle distribution by means of krill individual induction, foraging and diffusion motion, and by combining with genetic algorithm, the particles are concentrated in the high likelihood region and the particle diversity is also enhanced. Shih-ming Chen, XiaoJuan et al.[10] proposed an improved particle filter based on the gravitational field algorithm (GPA-PF) ,which treats particles as dust and takes the global optimal value after sampling as the central dust. Other particles affected by the movement factor and rotation factor of central dust to optimizes the distribution of particles. The particle set is concentrated in the position with a larger posterior probability density, thereby improving the filtering accuracy and particle diversity. In the original gravitational field algorithm[11], when the global optimal value guides the particle movement, it is possible to generate a new global optimal value. Moreover, for the assignment of the movement factor and rotation factor, the approach taken by Chen Shiming et al. is to compare the distance between the central particle and the current particle with the set threshold. And the value is assigned according to the comparison result, which reduces the diversity of particles to a certain extent.

In response to the above problems, this paper proposes an improved gravitational field algorithm to optimize particle filtering. First, the gravitational field algorithm is used to optimize the particle filter resampling process, so that the particle set is quickly distributed in the Gaussian region, solving the problem of particle weight degradation and refines the range of the assignment of the actuation factor and the rotation factor. While keeping the particles moving to the high likelihood region, the particle diversity is improved and improved the loss of particle diversity due to resampling, thereby increasing the filtering accuracy of the algorithm.

2 PARTICLE FILTER

The particle filter algorithm belongs to the theory category of nonlinear Bayesian estimation[12]. It approximates the probability density function of the random variable of the system through a set of weighted particle sets, and adopts Monte Carlo thought instead of the integral operation to obtain the minimum estimation of the system state variance.

The standard particle filter process is mainly composed of initialization, importance sampling, resampling, state estimation and other steps. The particle filter algorithm process is as follows:

1) Initialization: k =0, randomly sample N particles,

and the weight of each particle is $\frac{1}{N}$, The sampled particle set is as follows $\{x_0^i, \frac{1}{N}\}_{i=1}^N$.

2) Importance sampling: select the importance function at k time for sampling, and the importance density function is as follows:

$$q(x_k^i \left| x_{k-1}^i, z_k \right.) = p(x_k^i \left| x_{k-1}^i \right.)$$

* MERGEFORMAT (1)

3) Calculate the weight of the sampled particles:

$$\tilde{w}_t^i = \tilde{w}_{t-1}^i \frac{p(z_t / \tilde{x}_t^i) p(\tilde{x}_t^i / \tilde{x}_{t-1}^i)}{q(\tilde{x}_t^i / x_{t-1}^i)}$$

* MERGEFORMAT (2)

4) Weight normalization:

$$w_t^i = \tilde{w}_t^i / \sum_{i=1}^N \tilde{w}_t^i$$

* MERGEFORMAT (3)

5) Resampling: Since the variance of the importance weight increases randomly over time, the weight of particles is concentrated on a few particles. Even in the late iteration, there may be only a non-zero weight. The particle set cannot represent the actual posterior probability density, which is the particle degradation problem. The introduction of resampling can effectively solve the problem of particle weight degradation.

For the judgment method of weight degradation, the effective particle number is adopted as its judgment criterion.

$$\tilde{N}_{eff} = \frac{1}{\sum_{i=1}^N (\tilde{w}_t^i)^2}$$

* MERGEFORMAT (4)

Setting the threshold N_{thres} , when $N_{thres} \le \tilde{N}_{eff}$. That is, the effective number of particles is larger than the threshold, no resampling will be conducted. The resampling strategy is as follows: while keeping the number of particles unchanged, copy particles with larger weights, reduce copying or even discard particles with smaller weights; otherwise, perform resampling strategy is adopted.

6) State output:

$$\tilde{x}_t = \sum_{i=1}^N w_t^i x_t^i$$

* MERGEFORMAT (5)

The above is the complete particle filtering process. The classical particle filter algorithm introduces a resampling strategy to solve the problem of particle weight degradation, but this will also cause the possibility of loss of particle diversity. In order to simplify the calculation steps, the importance density is selected as the prior probability density function, but this method without considering the current observations, the sample obtained by the importance density function sampling has a large deviation from the sample obtained by the true posterior probability sampling in a strong noisy environment, which will seriously affect the filtering accuracy. Therefore, this paper will optimize the particle filter algorithm for the above problems.

3 GRAVITATIONAL FIELD ALGORITHM

The gravitational field algorithm(GFA) was proposed in the doctoral thesis of Zheng Ming[11] in 2012. This algorithm is mainly to simulate a series of celestial mechanics, especially the Solar Nebular Disk Model (SNDM), and use mathematical models to establish and use it. The effect of multi-peak function optimization is particularly outstanding. The idea of gravitational field algorithm is derived from the theory of planetary formation: solar nebular disk model (SNDM). The core idea of the GFA is that all feasible solutions distributed randomly or according to prior knowledge are represented by corresponding dust, and to add a weight to all dust (feasible solutions): quality. The global optimal solution is obtained by calculating the movement factor and rotation factor designed by the GFA. The main steps of the algorithm are as follows: initialization of dust, action of gravity factor, repulsive action of rotation factor, judgment of completion of iteration, and output of final solution.

Step1: Initialize the dust group. According to the pri or knowledge distribution, N feasible solutions are ra ndomly selected as dust from the feasible region, an d the dust set formed after initialization is $\{x_k^i\}_{i=1}^N$. A ccording to the observation equation, all the predicte d dust values were compared with the values at the current moment. The point with the smallest distan ce between the predicted value and the observed val ue at the current moment was taken as the center d ust x_{best} 。

Step2: The center dust attracts the movement of the surrounding dust. The center dust attracts the surro unding dust to move to the high-likelihood area. In this process, the surrounding dust moves towards the center dust by the gravitational force. This moveme nt is unidirectional and the center dust does not mo ve, which is different from the real physical model. The movement formula is as follows:

$$P_i = M \times \text{dis}A_i$$

* MERGEFORMAT (6)

In the above formula, P_i value represents the distance moved by the surrounding dust under the action of gravity; M represents the weight value of the moving distance. Taking $M = 0.0618$, which is exactly the $\frac{1}{10}$ of the golden ratio coefficient; $disA$ represents the distance between the center dust and surrounding dust. In one-dimensional and two-dimensional space, the Euclidean distance will be taken as the distance value of the dust space, but in the multidimensional space, the calculation of distance uses the direct minus method(DMM). That is, the distance value of the multidimensional space is decomposed into the distance value on the one-dimensional number axis.

It can be seen from the above formula that if the current surrounding dust position is x_i , the position formula after being attracted by the center dust is as follows:

$$x_j = x_i + P$$

* MERGEFORMAT (7)

$$x_i + M \times disA_i$$

* MERGEFORMAT (8)

Step3 : The rotation factor forms a repulsive force. Similar to SNDM, in the process of dust rotation, the center dust will repel surrounding dust due to its rotation. The rotation factor f is determined by the distance between the center dust and surrounding dust. The greater the distance, the smaller the f . On the country, the larger the f . That is, the rotation coefficient is constantly changing with the operation of the GFA. Moreover, it is not wise to use a uniform rotation coefficient for all surrounding dust. The best way is to set an independent rotation coefficient for each surrounding dust to highlight the relationship between the rotation coefficient and distance[11].

The model of center dust throwing dust under the action of rotation factor is as follows:

$$Q_i = f \times \sqrt[3]{disB_i}$$

* MERGEFORMAT (9)

In the formula, Q_i represents the distance that the surrounding dust moves under the action of the rotation factor; f represents the rotation factor, where $f_{\max} = 0.3$, $disB_i$ is the distance between the center dust and surrounding dust after Step2.

The update formula of surrounding dust location is as follows:

$$x'_j = x_j - Q_i$$

* MERGEFORMAT (10)

Where x'_j represents the new position of surrounding dust, and x_j represents the position of the surrounding dust after being attracted by the central dust.

Step4: judge whether it is over. If it is over, the optimal value will be generated,; otherwise, enter Step2.

The above is the main step of the gravitational field algorithm. By simulating the nebular motion, take the global optimal value as the center dust to attract the movement of surrounding dust, and throwing out the surrounding dust by the rotation factor, but make all the dust move towards the maximum likelihood region as a whole.

4 IMPROVED GRAVITATIONAL FIELD ALGORITHM TO OPTIMIZE PARTICLE FILTER

Although the process of improving particle filtering based on gravitational field algorithm(GFA-PF) has been realized in literature[10,13], but through a detailed analysis of the improvement process of GFA-PF, there still has the possibility of optimization, so this paper will optimize from the following two aspects, through the optimization of the gravitational field algorithm, the improved gravitational field algorithm optimization particle filter (Improved-GFA-PF, I-GFA-PF) will be realized. The process will not be repeated in this article. For details, please refer to the literature [10], [13].

4.1 Improved mobile factor evaluation criteria

In the literature [10], the movement factor is set as follows: first, calculate the direct distance dis_i between the surrounding dust and central dust, and set $disA_i = abs(dis_i)$. If $disA_i < 0.5$, then $disA_i = 0$; otherwise, bring it into the movement formula.This method maintains the diversity of particles to a certain extent. Since the distance between the surrounding dust (particles) and the central dust (particles) is small in the later iteration of the algorithm, all dust are concentrated in the same region, the adoption of $disA_i < 0.5$ increases the particles diversity and reduces the waste of computing resources. However, when the system is in a complex environment and strong noise scene, after the surrounding dust was attracted by the central dust, there will be a problem that the error between the predicted value and the true value is still large. Therefore, different moving factor evaluation criteria are adopted for different dust (particles).

After calculating the direct distance dis_i between the surrounding dust and center dust, let $disA_i = abs(dis_i)$ and take clustering operation for all sets of absolute dust distances $\{disA_i\}_{i=1}^{N}$. As an unsupervised machine learning technique, clustering is based on a given similarity measure. The data is divided into several classes, so that the data has higher similarity in the same class, and lower data similarity between different classes[14]. This paper divides the dust distance collection into 4 categories. Determine the value of each cluster center after clustering, arrange the value in ascending order, and assign different moving distance weight values to the cluster where the cluster center is located. The larger the median value of the class is, the greater the distance weight value is.In this paper, the weight of the moving distance is taken as M , $1.2M$, $1.5M$, $2M$. This improvement generates more gravity for dust with a large distance from the center, that is, moves more distance. Moreover, different moving weight values are adopted for different kinds of dust, which not only increases the diversity of particles, but also improves the filtering accuracy of the algorithm under strong noise.

4.2 Adaptive repulsion setting

In [10], the particle repulsion is set as follows: first, calculate the direct distance dis_i between the surrounding dust and central dust after the gravitational force. To determine whether the movement factor is effective, let $disB_i = abs(dis_i)$. If $disB_i > 0.2$, then $disB_i = 0$. Otherwise, it is substituted into the model in which the center dust is thrown by the rotation factor. When $disB_i > 0.2$, the repulsive force generated by the central dust does not work in this method. Under strong noise, the number of dust (particles) satisfying this condition is extremely small. Although the particles are kept concentrated in the high-likelihood area, the diversity of particles is reduced to some extent. This article adopts the adaptive repulsion value setting. that is, after calculating the $disB_i$, calculate the mean value $meanB = \sum_{i=1}^{N} mean(disB_i)$ from the set of absolute distances between the surrounding dust and center dust, if $disB_i > 0.5meanB$, $disB_i > 0.5meanB$; conversely, perform the repelling operation. This improvement takes one-half of the average absolute value of the distance between the surrounding dust and center as the criterion, rather than the fixed value, which increases the number of particles to be rejected, namely, increases the diversity of particles.

4.3 Improved algorithm

Step1: Initialization: At $k=0$ moment, sample N particles from the initial population according to $x_0^i \sim p(x_0)$, and each particle weight is $\frac{1}{N}$.

Step2: Importance sampling: Select the importance function at k time for sampling, and sample N particles.

Step3: Weight calculation and normalized weights.

Step4: Improved gravitational field algorithm to optimize resampling:

1) Take the particle represented by the maximum weight as the global optimal value;

2) Regarding the particle represented by the global optimal value as the central dust, and other particles as the surrounding dust, calculate the absolute value of the distance between the central dust and the surrounding dust, the formula is as follows:

$disA_i = abs(dis_i)$

3) Through 3.2 operation, the center dust attracts the surrounding dust.

4) Calculate the absolute value of the distance between the center dust and the surrounding dust after the dust moves. The formula is as follows:

$disB_i = abs(dis_i)$

5) Perform operation 3.3, the center dust will throw out the surrounding dust selection.

6) Obtain new particle distribution until the end of iteration, and recalculate the normalized weight of each particle.

7) Calculate the number of effective particles according to formula (4) and determine whether to resampling.

Step5: The state output is realized by formula (5).

5 EXPERIMENTAL RESULTS AND ANALYSIS

The experimental hardware is a desktop computer (Intel i5 processor, 4G running memory), and the experimental environment is MATLAB 2016a. The improved algorithm (I-GFA-PF) proposed in this paper is compared with the improved particle filter algorithm based on gravitational field algorithm (GFA-PF) and the classical particle filter algorithm (PF).

The state equation and observation equation of the system adopted in this paper are:

$$x(t) = 0.5x(t-1) + \frac{2.5x(t-1)}{1+x(t-1)^2} + 8\cos[1.2 x(t-1)] + w(t-1)$$

* MERGEFORMAT (11)

$$z(t) = \frac{x(t)^2}{20} + v(t)$$

* MERGEFORMAT (12)

This model is a typical nonlinear non-Gaussian system model, $w(t)$, $v(t)$ is zero mean Gaussian noise. For the performance of the filtering algorithm, the parameter root mean square error($RMSE$)is used as the evaluation index of the algorithm, and the formula is as follows:

$$RMSE = \left[\frac{1}{T} \sum_{t=1}^{T} (x_t - \hat{x}_t)^2 \right]^{\frac{1}{2}}$$

* MERGEFORMAT (13)

Table 1 Effective particle number comparison

time	1	2	3	4	5
GFA-PF	69.77	70.03	69.67	69.92	69.61
I-GFA-PF	81.21	81.66	82.13	82.16	82.04

In order to explore the improvement of the particle degradation of the improved algorithm, the GFA-PF and I-GFA-PF algorithms were tested 5 times under the same noise environment and the iterations number of the gravitational field algorithm when the particles number were 100. It can be seen from Table 1 that the number of effective particles of the I-GFA-PF has been improved relative to the GFA-PF, that is, the I-GFA-PF solves the problem of PF particle weight degradation, and compared to GFA-PF, the I-GFA-PFr is more effective.

Since the particle filter resampling process will cause the loss of particle diversity. This article sets the sampling period T=100, and takes the sampling time k=20, k=50, and k=95 respectively to represent the early, middle, and late sampling of the improved algorithm. The experimental results are shown in Fig.1, Fig.2, and Fig.3.

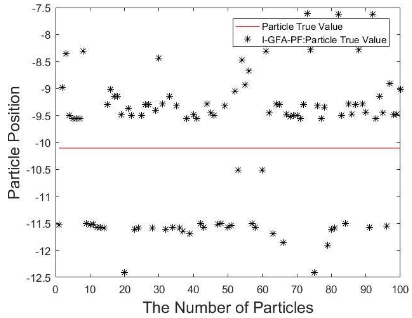

Fig.1. k=20, particle distribution

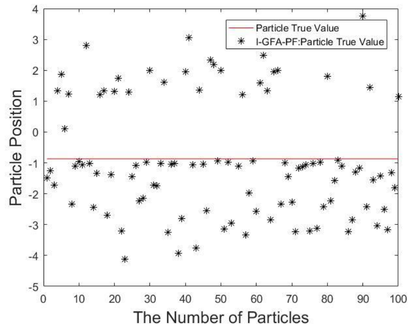

Fig.2. k=50, particle distribution

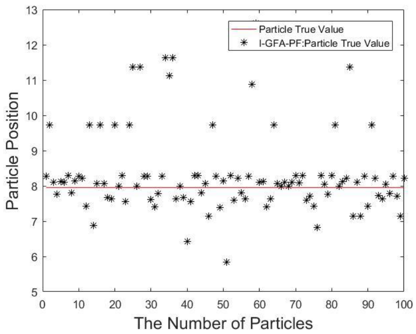

Fig.3. k=85, particle distribution

From the above figures,it can be seen that the improved algorithm gradually increases the particles clustered near the true value over time, and in the late iterations, most particles cluster near the true value. But there are still a few particles distributed far away from the true value. This is because compared to PF, improved algorithm introduces the gravitational field algorithm to optimize the distribution of the sampled particles, and refines the movement factor and rotation factor. Therefore, while the sampled particle collection moves to the high-likelihood region, the diversity of particles is maintained, the sampled particle set is more similar While the area moves, the diversity of particles is maintained.

To verify the filtering accuracy of the improved algorithm, takes the number of sampling points are 100, the sampling period is T=100, the number of iterations of the gravitational field algorithm are 8, and the noise variance of the system state equation is set to 10, the noise variance of the system observation equation is set to 1. Compare the classic particle filter algorithm (PF), the optimized particle filter algorithm based on gravitational field (GFA-PF), and the improved algorithm(I-GFA-PF), the experimental results are shown in the figure below:

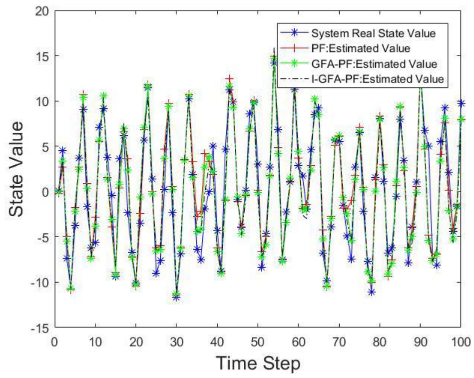

Fig.4. system state estimation

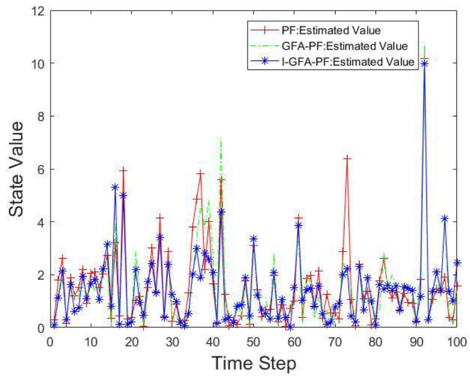

Fig.5. absolute value of estimated error

As can be seen from Fig.4 above, compared with the classical algorithm (PF) and optimized particle filter based on the gravitational field algorithm (GFA-PF). The improved algorithm has the highest coincidence degree with the real value of the system in the state estimation. And in Fig.5, the error absolute value of the improved algorithm is relatively stable.The improved algorithm has small overall error compared with PF and GFA-PF, this is because the improved algorithm optimizes the system importance density function and makes the particle set tend to move in high likelihood region. And compared with GFA-PF, the improved algorithm adds the feature that the gravitational field algorithm will change the global optimal value in the iterative process, and more refined assignment of movement factor and rotation factor, so the algorithm proposed in this paper has the best improvement effect.

Table 2 Comparison of mean square error values of three algorithms

algorithm	N=20	N=50	N=80
PF	4.851451	4.588581	4.280951
GFA-PF	4.677862	4.200904	4.095323
I-GFA-PF	4.255794	4.148959	3.875689

Table 2 shows that the comparison of root mean square error of three algorithms with different number of particles under the same number of sampling points, noise intensity, and number of iterations of the gravitational field algorithm (the relevant parameter settings are the same as the above algorithm filtering accuracy comparison experiment). We randomly conduct ten experiments and take the average value to avoid the contingency of the experiment. It can be seen from Table 2 that GFA-PF and the I-GFA-PF proposed in this paper, as the number of particles increases, the filtering accuracy gradually improves, and the algorithm running time gradually increases, which is consistent with the characteristic that the particle filter algorithm gradually converges as the number of particles increases. And it also can be seen that the improved algorithm has the highest filtering accuracy, and it still has a higher positioning accuracy when the number of particles is small. The reason is that the improved gravitational field algorithm makes the sampled particle set moved to high likelihood region. And for the refined movement factor and rotation factor, the particle position distribution is closer to the real value of the system during the movement process. Therefore, the improved algorithm increases the filtering accuracy.

6 CONCLUSION

This paper improves the algorithm proposed in Xiao Juan et al.[10,13]. The optimization of the gravitational field algorithm is based on optimizing the resampling of particle filter through the gravitational field algorithm.In this process, the movement factor and rotation factor are refined, the problem of particle weight degradation is alleviated, and the particle diversity is effectively improved, thereby improving the filtering accuracy. From the experimental analysis, it can be seen that the improved algorithm effectively solves the problem of particle weight degradation. Compared with the original improvement idea, the algorithm proposed in this paper increases the diversity of particles, and then achieves the improvement of filtering accuracy.

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