A New Particle Filter Target Tracking Algorithm Based on Genetic Algorithm

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Abstract: Aimed to problem that particles exist degradation in particle filter (PF) algorithm for target tracking which is used in Wireless Sensor Networks, a new particle filter target tracking algorithm (GPF) based on genetic algorithm was proposed in this paper. First, based on the description of the PF algorithm, the factors that affect the degradation were analyzed, which were importance function and re-sampling technique. Then, a new importance function which can make the current measured value take effect was constructed and the re-sampling technique was mended by using genetic algorithms in the GPF. Finally, the simulation tracking results showed that the GPF algorithm has better tracking accuracy than that of PF.

Keywords: Genetic algorithm, particle filter, target tracking, wireless sensor networks.

1. INTRODUCTION

Target tracking model of Wireless Sensor Networks (WSN) usually is nonlinear and non-Gaussian model [1, 2]. PF algorithm is a filtering method that based on a sequential Monte Carlo [3]. As it attached to approximate the posterior probability distribution by using a series of random particles with weights, it does not subject to non-linear, non-Gaussian constraints. Thus, it has been widely used in target tracking in WSN [4], fault diagnosis [5], economic forecasting [6] and other fields. However, the algorithm has a serious degradation [7], thereby affecting the tracking effect. PF algorithm is improved in Literature [8-10]. In this paper, based on PF algorithm, GPF was proposed which is suitable for wireless sensor networks.

2. BASIC PF ALGORITHM

2.1. PF Algorithm

Algorithm flow chart is shown in Fig. (**1**).

According to the algorithm flow chart, step of particle filter as follows:

1) Initialize. N point set of particles $\{x_0^i, w_0^i\}_{i=1}^N$ are obtained by initializing probability density distribution $p(x_0)$. Initialize the weights of all the particles as $w_0^i = 1/N$ X;

2) Particle state predict. At time k ($k = 1,2,3...$), predicted particle state at time k through the movement of objects

kinetic model $P(x_k | x_{k-1} = x_{k-1}^i)$, produce set of particles at k moment, particle weights are $w_k^i = 1/N$.

3) Update the particle. Using equation (1) to update weights of each particle in particle set at time k .

$$w_k^i = w_{k-1}^i \frac{p(z_k | x_k^i) p(x_k^i | x_{k-1}^i)}{q(x_k^i | x_k, z_k)} \tag{1}$$

4) Re-sample. Define valid sampling scale as $N_{eff} = 1/\sum_{i-1}^N w_i$. If $N_{eff} < N_{th}$, (N_{th} is a threshold) then re-sampled.

2.2. Particle Degradation

Particle degradation is a inevitable phenomenon in PF algorithm. Iteration of the loop, in addition to a particle, the other particle weights is negligible [11]. An important technology of reducing the particle degradation is selection of importance functions and re-sampling [12].

1) The importance function

Importance function affects the efficiency of the algorithm and the degradation rate of weight coefficients. Make importance functions easy to sample and minimum variance weights are the two principles of choosing importance function. Importance function should be as close as possible to the system status posterior probability, which can reduce the variance of the importance weights and make variance of its weights the smallest.

2) Re-sample

Re-sampling is another factor affecting to reduce particle degradation. The aim is to leave a large particle weights,

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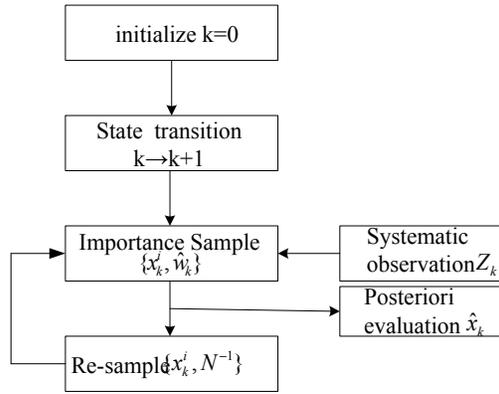
Fig. (1). PF algorithm flow chart.

reduce the number of particles with smaller weights. When reduce to a threshold, namely, the apparent degradation appear, re-sample the existing set of samples and generate a new set of samples.

3. GPF ALGORITHM

3.1. Mend the Importance Function

In order to reduce the particle degradation mitigation in the PF, first, mend the importance function of PF. Select importance function that can make the current measured value function [13]. Importance function is approximation of the posterior distribution, when the likelihood function compared with the transition probability distribution is too concentrated, closer the posterior density than prior density. Therefore, on the basis of the likelihood function using a new approximation, can play new tracking results.

Construction of importance function:

Order $m_k = (x_k)^2$, $p(m_k / z_k)$ is the prior distribution probability density function of m_k, repeat sampled from $p(m_k / z_k)$ until $m_k \geq 0$. m_k is recorded as $m_k^i \sim p(m_k / z_k)$. Using $p(x_k / m_k^i)$ to construct importance function, at this point, x_k^i depends only on z_k, nothing to do with x_{k-1}^i. Thus launched $q(x_k^i / x_{k-1}^i, z_k) = p(x_k^i / m_k^i)p(x_k^i / z_k)$。

Seeking $\dfrac{p(x_k^i / z_k)}{p(m_k^i / z_k)}$ according weight update equation

$w_k^i \propto w_{k-1}^i p(x_k^i / x_{k-1}^i) \dfrac{p(x_k^i / z_k)}{p(m_k^i / z_k)}$. Its true value may be considered as proportional. $p(x_k / z_k)$ and $p(m_k / z_k)$, respectively, quadrature for x_k and m_k. Between the ratio of the probability density is proportional to $\left| \dfrac{dm_k}{dx_k} \right| = 2x_k$. At this time, weight update equation is shown in equation (2).

$$w_k^i \propto w_{k-1}^i p(x_k^i / x_{k-1}^i) \frac{p(x_k^i / z_k)}{p(m_k^i / z_k)} \tag{2}$$

$$\propto w_{k-1}^i p(x_k^i / x_{k-1}^i)x_k^i$$

So after sampling, a new importance function is obtained.

3.2. Mend Re-sample by Using Genetic Algorithm

First, according to the weight of the particle, N new particles are obtained from the old set of $\{x_k^i, w_k^i\}_{i=1}^N$ by roulette approach with the select probability of p_s.

Secondly, randomly selects two correspond articles from the new set of particles $\{\hat{x}_k^i, \hat{w}_k^i\}_{i=1}^{N_s}$ and the old set of particles, $\{x_k^i, w_k^i\}_{i=1}^N$, With probability p_c cross processing, resulting in producing two new particles $\hat{x}_k^{i'}, \hat{x}_k^{i''}$, alternatively replaced $\hat{x}_k^i$, get a new set of particles $\{\hat{x}_k^i, \hat{w}_k^i\}_{i=1}^{N'}$, crossover operation generates $N_c = N * p_c$ new particles.

Finally, particles $\{\hat{x}_k^i, \hat{w}_k^i\}_{i=1}^{N'}$ which are obtained through selection and crossover are mutated with mutation probability p_m. Randomly select a particle $\hat{x}_k^i$ from particles set $\{\hat{x}_k^i, \hat{w}_k^i\}_{i=1}^{N'}$ to do mutation operation to get a new particle $\hat{x}_k^{i'}$, With $\hat{x}_k^{i'}$ replace $\hat{\mathcal{x}}_k^i$, get new particle set $\{\hat{x}_k^i, \hat{w}_k^i\}_{i=1}^{N''}$, mutation operation generates $N_m = N * p_m$ new particles.

As randomly selected rule make the same probability of each particle being selected, increasing the particle crossover, mutation opportunities to mend poor particle problem. Cross is concentrated in while selecting both the old and new particles, not only the good genes to be retained, but also mends the efficiency of the cross.

3.3. Steps of GPF Algorithm

1) Initialization. N-point set of particles $\{x_0^i, w_0^i\}_{i=1}^N$ are obtained by initial probability density distribution $p(x_0)$. Initialize the weight of all the particles is $w_0^i = 1 / N$;

2) Particle state prediction. At time k ($k = 1,2,3...$), predict particle state at time k by dynamic model $P(x_k | x_{k-1} = x_{k-1}^i)$ of the movement of objects.

3) Particle weight. Select importance density as forward probability function of the target motion. The update formula show as equation (3).

$$w_k^i \propto w_{k-1}^i p(x_k^i / x_{k-1}^i) \frac{p(x_k^i / z_k)}{p(m_k^i / z_k)} \tag{3}$$
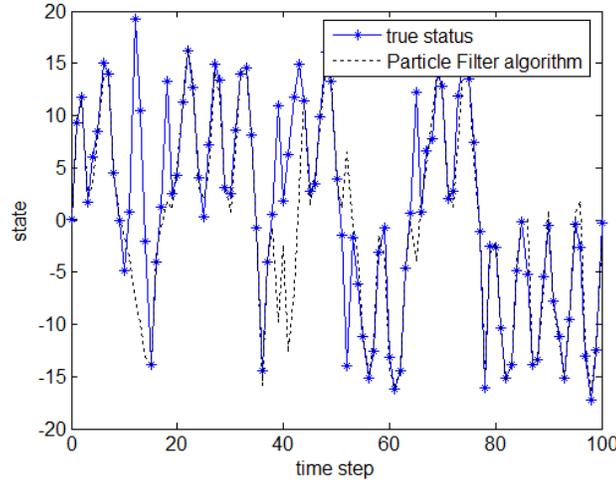
$$\propto w_{k-1}^i p(x_k^i / x_{k-1}^i)x_k^i$$

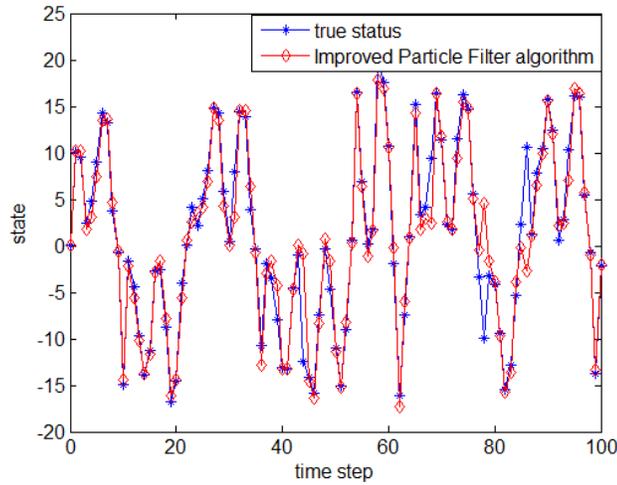**Fig. (2).** Tracking simulation diagram of PF.

Fig. (3). Tracking chart of GPF algorithm.

4) Genetic manipulation of particles. Use genetic algorithm to re sample the set of particles which produce in the step 3). N particles with maximum weight are selected from the results $\{\hat{x}_k^i, \hat{w}_k^i\}_{i=1}^{N''}$ of crossover and mutation. Then go to Step (2), for the next forecast.

4. SIMULATION AND ANALYSIS OF ALGORITHMS

The simulation uses the used system equations to experiment, show as the equation (4).

$$\begin{cases} x_k = f(x_{k-1}, k) + u_{k-1} \\ z_k = x_k^2 / 20 + v_k \end{cases} \tag{4}$$

Among   ,

$f(x_{k-1}, k) = x_{k-1}/2 + 25 x_{k-1}/(1 + x_{k-1}^2) + 8\cos(1.2k)$ both u_{k-1} ,

and v_k is a mean-variance matrix, respectively, is zero-mean Gaussian random variables of Q_{K-1} and R_K. $Q_{K-1} = R_k = 1$, $T = 100$.

Elementary particle filter algorithm and the algorithm proposed in this paper use the above nonlinear model of moving target tracking to simulate, and simulate of the root mean square error between several algorithms. Root mean square error is defined by using equation (5).

$$RMS = \sqrt{\sum_{i=1}^{N} \frac{1}{T}(\hat{x}_k - x_k)^2} \tag{5}$$

Where, N is the number of simulations and the value is 100; T is the sampling period; $\hat{x}_k$ and x_k respectively represent algorithms tracking results and system true status. The simulation results are shown in Fig. (2) and Fig. (3).

Fig. (2) shows the tracking simulation diagram of the basic *PF* algorithm. It can be seen from the figure that the basic PF algorithm can approximate the real results when it tracks moving targets, but a great error in some sampling points.

Fig. (3) shows tracking simulation diagram of the GPF algorithm. It can be seen from the simulation results that the

Table 1. Comparison of RMSE of two algorithms.

	Algorithm	
	PF Algorithm	**GPF Algorithm**
error	4.9782	2.7063

GPF algorithm can better approximate the real result than the basic PF and a small error in some sampling points. Table **1** shows the comparison of tracking error of the two algorithms. As the error parameters of the system equations are random variables, the error values are not a determined value, but still it is clear that the advantages of GPF.

CONCLUSION

PF target tracking algorithm used in wireless sensor networks was researched in this paper. An new particle filter tracking algorithm (GPF) was proposed to solve particle degradation problem. GPF algorithm re-constructed the importance of the function and mended re-sample with genetic algorithm. Finally the simulation showed the new particle filter algorithm had a new tracking effect.

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CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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