New clone particle swarm optimization-based particle filter algorithm and its application

Yuming Bo\textsuperscript{1}, Zhimin Chen\textsuperscript{1}, Jie Zhang\textsuperscript{1}, Jianliang Zhu\textsuperscript{1}

\textsuperscript{1}School of Automation, Nanjing University of Science and Technology, Nanjing, 210094, China

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Abstract: A new particle filter algorithm based on new Clone particle swarm optimizer NCPSO-PF is presented in this paper in order to solve the problem of low precision and complicated calculation of particle filter based on particle swarm optimization algorithm (PSO-PF). The algorithm enables the particles to fit the environment better and then reach the goal of global optimization through orthogonal initialization, clonal selection and local searching of self-learning. Finally different models are used for simulation experiment and the results indicate that this new algorithm improves the operation speed and precision of practical engineering application.

Keywords: particle filter; particle swarm optimization; Clone; orthogonal

1. Introduction

Particle filtering is a sequential Monte Carlo methodology where the basic idea is the recursive computation of relevant probability distributions using the concepts of importance sampling and approximation of probability distributions with discrete random measures [1]. It is widely applied to positioning and navigation of non-Gaussian noise and non-linear system, fault diagnosis [2], target tracking and mode identification field [3] as its state function and observation function has no non-linear hypothesis. Nevertheless, PF may confront with the problem of weight degradation [4] which if solved by resampling method may result unavoidable particle impoverishment [5-6]. As a result, the filtering precision is influenced.

PF based on Intelligent Optimization Algorithms conduces to significant improvement of particle degradation in PF and great enhancement of precision [7]. Particle swarm optimization-based PF (PSO-PF) is a typical representative of Intelligent Optimization Algorithm which introduces PSO algorithm into PF. Through introduction of the latest measurement value to the sample distribution, along with the utilization of PF algorithm for sampling process optimization and constantly update of particle speed, the sample distribution is inclined to move to the area with higher posterior probability [8]. PSO-PF improves the particle degradation of PF and is easier for actualization. Unfortunately PSO-PF is a process of iterative optimization which will prolong the calculation time because of the high iterative frequency [9]. Moreover, PSO-PF may be easily trapped into local optimization, influencing the precision and stability of practical engineering application [10].

A new particle filter algorithm based on new Clone particle swarm optimizer NCPSO-PF is suggested in this paper. This algorithm utilizes orthogonal strategy and clone particle swarm algorithm for optimization, enhancing the quality and diversity of particles. The experimental results prove that NCPSO-PF improves the efficiency of particle filter.

2. PSO-PF algorithm

2.1. Basic PSO algorithm

PSO is an intelligence optimization algorithm imitating birds’ clustering movement. It is widely applied to target tracking, positioning and navigation, mode identification etc. by virtue of its advantages of simple concept, ease in actualization, fewer parameters, and effectiveness in solving complicated optimization and so on. PSO algorithm can be expressed as follows [11]: to randomly initialize a
particle swarm whose number is m and dimension is n, in which the ith particle’s position is \(x_i = (x_{i1}, x_{i2}, \ldots, x_{in})\) and its speed is \(v_i = (v_{i1}, v_{i2}, \ldots, v_{in})\). During each iteration, the particles can renew their own speed and position through partial extremum and global extremum so as to reach optimization. The update formula is:

\[
V_{i} = w \times V_{i} + c_1 \times \text{Rand()} \times (P_{i} - X_{i}) + c_2 \times \text{Rand()} \times (G - X_{i})
\]

\[
X_{i+1} = X_{i} + V_{i}
\]

where \text{Rand()} is a random number within interval (0,1), \(w\) is the inertia coefficient, \(c_1\) and \(c_2\) are learning factors.

2.2. Description of standard PSO-PF algorithm

The importance sampling process of conventional PF is suboptimal, whereas the incorporation of PSO algorithm will optimize the sampling process of PF, allow the weight of particle sets are more inclined to high likelihood region, accordingly solving the problem of particle impoverishment, and conducing to reduction of particle numbers according solving the problem of particle impoverishment. The importance sampling process of conventional PF is mainly consists of genetic recombination and genetic mutation. In order to facilitate the communication of useful information among individuals and to enhance the uniformity of progeny individuals, orthogonal recombination algorithm is employed here to recombine the cloned individuals by probability.

(1) Genetic recombination. Given the genetic recombination operator \(F^c\), and \(C(k) = \{c^1(k), c^2(k), \ldots, c^{|S_{size}|}(k)\}\) as the population after recombination.

Taking two parental particles \(b_1 = (b_{11}, b_{12}, \ldots, b_{1n})\) and \(b_2 = (b_{21}, b_{22}, \ldots, b_{2n})\) into consideration, a sub-space \([l, u]\) is determined in accordance with the following equation:

\[
\left\{\begin{array}{l}
\{l = \text{min}(b_{11}, b_{21}), \text{min}(b_{12}, b_{22}), \ldots, \text{min}(b_{1n}, b_{2n})
\}
\{u = \text{max}(b_{11}, b_{21}), \text{max}(b_{12}, b_{22}), \ldots, \text{max}(b_{1n}, b_{2n})
\}
\end{array}\right.
\]

First of all each of the region in Space \([l, u]\) is quantified into \(Q\) levels, and the difference between two neighboring levels are always the same. \(\beta_i = (\beta_{1i}, \beta_{2i}, \cdots, \beta_{Qi})\) is defined as follows:

\[
\begin{align*}
\text{min}(l_{ij}, u_{ij}) + (j - 1) \times \frac{(u_{ij} - l_{ij})}{Q - 1}, & \quad 1 \leq j \leq Q - 1 \\
\text{max}(l_{ij}, u_{ij}), & \quad j = Q
\end{align*}
\]

\[F - 1\] integer will be generated, \(k_1, k_2, \ldots, k_{F - 1}\), and \(1 < k_1 < k_2 < \cdots < k_{F - 1} < n\) is met. Then for any particles \(x = (x_1, x_2, \ldots, x_n)\), the following \(F\) factors will be generated.

\[
f_1 = (x_1, \cdots, x_{k_1}), f_2 = (x_{k_1 + 1}, \cdots, x_{k_2}), \cdots, f_F = (x_{F - 1 + 1}, \cdots, x_n)
\]
$Q$ levels of factor $f_i$ are

$$
\begin{align*}
&f_i(1) = (\beta_{k_i-1+1,1}, \beta_{k_i-1+2,1}, \cdots, \beta_{k_i,1}) \\
&f_i(2) = (\beta_{k_i-1+1,2}, \beta_{k_i-1+2,2}, \cdots, \beta_{k_i,2}) \\
&\cdots \\
&f_i(Q) = (\beta_{k_i-1+1,Q}, \beta_{k_i-1+2,Q}, \cdots, \beta_{k_i,Q})
\end{align*}
$$

The orthogonal matrix $L_M(Q^f) = [r_{ij}]M_2 \times F$ is used to generate the following $M$ particles:

$$
\begin{align*}
&\left\{ (f_1(r_{11}), f_2(r_{12}), \cdots, f_F(r_{1F}), ) \\
&\quad (f_1(r_{21}), f_2(r_{22}), \cdots, f_F(r_{2F}), ) \\
&\quad \cdots \\
&\quad (f_1(r_{QM}), f_2(r_{QM}), \cdots, f_F(r_{QM}), )
\right\}
\end{align*}
$$

Finally, an optimal particle is selected from $M$ particles as the clone progeny subject. Given $Q = 3, F = 4, M = 9$, and orthogonal matrix is marked as $L_0(3^4)$.

(2) Genetic mutation. AEA mutation strategy is used, letting $D(k) = \{d_1(k), d_2(k), \cdots, d_{\text{SIZE}}(k)\}$ the population after mutation, that is,

$$
d_j = \frac{f_{\text{fix}}(c_j^i \times 10^{f(\text{mod} \ 10 - md(10))})}{10^i} \quad i = 1, 2, \cdots, \text{SIZE}; j = 1, 2, \cdots, q
$$

where $i$ is the random number of $0 \sim 15$, $f_{\text{fix}}()$ is rounded down, $md(10)$ a random integer less than 10, whereas the probability of mutation is usually very small.

(3) Clone selection operator. Different from the selection operation in evolutionary operation, clone selection operator is to select the excellent individual from particle clone and to form new populations. Given $\forall i = 1, 2, \cdots, \text{SIZE}$, then:

$$
d_j^i(k) = \{d_j^i(k) \mid f(d_j^i), j = 1, 2, \cdots, q\}
$$

For probability $p^k(a_j(k) \cup a_i(k+1))$,

$$
p^k(a_j(k+1) = d_j^i(k)) = \begin{cases} 
1, & f(a_j(k)) > f(d_j^i(k)) \\
\exp\left(-\frac{f(a_j(k)) - f(d_j^i(k))}{a}\right), & f(a_j(k)) \leq f(d_j^i(k)) \text{and} \\
0, & f(a_j(k)) \leq f(d_j^i(k)) \text{and} f(a_i(k+1)) \text{is the best antibody.}
\end{cases}
$$

(4) Self-learning operator. During the clone operation of particle swarm, it searches in a relatively large range, to avoid the loss of optimal solution, self-learning local searching of optimal individuals after clone selection is performed in this paper. For the optimal individual $\hat{a}(k) = (\hat{a}_1(k), \hat{a}_2(k), \cdots, \hat{a}_n(k))$, first of all a self-learning population $L$ is generated with size $L_{\text{SIZE}}$, then $L$:

$$
L = \begin{cases} 
\hat{a}(k), & i = 1 \\
\text{New}_i, & \text{others}
\end{cases}
$$

wherein $\text{New}_i = (e_{i,1}, e_{i,2}, \cdots, e_{i,n})$ is generated according to the following equation:

$$
e_{i,k} = \begin{cases} 
\hat{a}_{i,k} \cdot U(1 - \text{radius}, 1 + \text{radius}) & k = 1, 2, \cdots, n, \text{in which radius} \in [0,1] \text{ denotes searching semi-diameter, } U(1 - \text{radius}, 1 + \text{radius}) \text{ denotes the random number in interval } [1 - \text{radius}, 1 + \text{radius}]. \\
\text{Min}_i = (m_1, m_2, \cdots, m_n), \text{the individual with optimal fitness in } L, \text{ e.g. } \text{Min}_i \in L, \text{ and for any individual } L_i \in L \text{ in a small population, we have } f(L_i) \geq f(\text{Min}_i) \text{, if } L_i \text{ meets } f(L_i) = f(\text{Min}_i), \text{ then it is a winner and will be preserved in the self-learning population, or otherwise a loser that should die. The eliminated individuals will be occupied by new individuals New} = (e_{\hat{a}_1}, e_{\hat{a}_2}, \cdots, e_{\hat{a}_n}) \text{ generated by } \text{Min}_i, \text{ wherein } P_0 \text{ is the probability given.}
\end{cases}
$$

$$
e_{i,k} = \begin{cases} 
m_k + d \times (m_k - L_{\text{radius}}), k = 1, 2, \cdots, n, & \text{if } U(0,1) < P_0 \\
(m_1, m_2, \cdots, m_{i-1}, m_i, m_{i+1}, \cdots, m_n), & \text{else}
\end{cases}
$$

where $d$ is the random variable within range $[0,1]$. Finally, Gaussian mutation of the individuals in self-learning population is carried out, and the learned individual is replaced by optimal individual.

4. Process of NCPSO-PF

(1) Take $N$ particles $\{\hat{x}_{i,k} | i = 1, \ldots, N\}$ as samples from importance function at the initial time. The importance density function is expressed in equation (18)

$$
\hat{x}_{i,k} \sim q(\hat{x}_{i,k} | \hat{x}_{i,k-1}, z_k) = p(\hat{x}_{i,k} | \hat{x}_{i,k-1})
$$

Giving the fitness function:

$$
Y = \exp[-\frac{1}{2R_k}(z_{\text{New}} - z_{\text{Pred}})]
$$

Where $z_{\text{New}}$ is the latest observed value, $z_{\text{Pred}}$ is the predictive observed value.

(2) calculate the importance value:

$$
w_{i,k} = w_{i,k-1}P(z_k | \hat{x}_{i,k-1}) = w_{i,k-1}P(z_k | \hat{x}_{i,k})
$$

(3) Updating the speed of particle swarm $A(k)$, then we have $\hat{A}(k)$

(4) Replace $T\%$ relatively undesirable individuals with $T\%$ desirable ones in $A(k)$, and $A(k) \leftarrow \hat{A}(k)$

(5) Perform clone operation against particle swarm $A(k)$, including clone recombination and clone mutation, then $\hat{A}(k)$

(6) Perform immune gene operation against particle swarm $\hat{A}(k)$, including clone recombination and clone mutation, then $D$. 

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(7) Perform clone selection against $D$, then $A^*(k)$.

(8) Force the self-learning operator to take effect on the optimal individual of $A^*(k)$ and then to upgrade the optimal individual.

(9) Assuming $x_i$ is the individual extreme value of the current particle, $pb_i$ the optimal solution at $t$ time of particle $i$, $g_{best}$ is the global optimal solution at $t$ time. Compare their fitness update $pb_i$ and $pg$:

$$
\begin{align*}
    pb'_i &= \begin{cases} 
        pb'_i, Y(t) < Y(pb'_i) \\
        x_i, Y(t) > Y(pb'_i)
    \end{cases} \\
    pg_k &\in \{x^1_k, x^2_k, x^{N}_k\} \\
    = &\max(Y(x^1_k), Y(x^2_k), \ldots, Y(x^{N}_k))
\end{align*}
$$

(10) When the optimal value of particle complies with the initially-set threshold value or algorithm reached maximum iteration times $\lambda$, it is indicated that the particles have been already distributed around the true values. By now particle optimization should be stopped. Else jump to step(3).

(11) Calculate the importance weight of the particles after optimization and perform normalization:

$$
\begin{align*}
    w^i_k &= w^i_{k-1} \frac{p(y_k|x^i_k)p(x^i_k|x^i_{k-1})}{q(x^i_k|x^i_{k-1}, y_k)} \\
    w^i_k &= w^i_{k-1} \sum_{i=1}^{N} w^j_k
\end{align*}
$$

(12) State output:

$$
\hat{x} = \sum_{i=1}^{N} w^i_k x^i_k
$$

5. Simulation experiment

5.1. Univariate nonstationary growth model

Choosing a univariate nonstationary growth model (UNGM), and the process model and measurement model of the simulated objects are given as follows:

$$
\begin{align*}
    x(t) &= 0.5x(t-1) + \frac{25x(t-1)}{1 + [x(t-1)]^2} + 8\cos[1.2(t-1)] + w(t) \\
    z(t) &= \frac{x(t)^2}{20} + v(t)
\end{align*}
$$

In which, $w(t)$ and $v(t)$ are zero-mean Gaussian noise. Since this system is highly non-linear and the likelihood function presents bimodal, it will be difficult for traditional filtering methods to deal with this system. By using PF, PSO-PF and NCPSO-PF, state estimation and tracking of this non-linear system are performed, and the formula of root-mean-square error is

$$
RMSE = \left[ \frac{1}{T} \sum_{t=1}^{T} (x_t - \hat{x}_t)^2 \right]^{1/2}
$$
tion result is presented in figure 5.1...5.4. After 500 times of Monte-Carlo simulation, result is given in Table 1.

5.2. Simulation model of white noise deconvolution filter

In practical engineering, the estimation of optimal output of deconvolution white noise is a common-seen problem. In this paper, PF, PSO-PF and NCPSO-PF are used to forecast the white noise of a randomly-selected system that is described as follows:

\[ x(t+1) = \begin{bmatrix} 1 & 0 \\ 0.3 & 0.5 \end{bmatrix} x(t) + \begin{bmatrix} -1 \\ 2 \end{bmatrix} w(t) \]  \quad (29)

in which \( w(t) = b(t)g(t) \) is Gaussian white noise. \( b(t) \) is the white noises with values 1 and 2. The probability for value acquisition is:

\[ P(b(t)) = \begin{cases} \lambda, & b(t) = 1 \\ 1 - \lambda, & b(t) = 0 \end{cases} \]  \quad (31)

\( \lambda \) is the probability of \( w(t) \) with a non-zero value. \( g(t) \) is the Gaussian white noise independent of \( b(t) \) with mean value 0 and variance \( \sigma^2_g \). In the simulation, \( \sigma^2_g = 0.1, \sigma^2_w = 0.1 \), and the simulation results are shown as following, in which the vertical axis of the solid line end point, and the vertical axis of round dot represents the estimated value.

Making a comparison between the simulation results shown in the figure, the estimation of white noise by PF...
Displays the lowest precision, and it fails to well predict the value of most of the state points, while the precision of two particle filters by PSO is improved significantly. As for NCPSO-PF, since it successfully preserves the diversity of population, it has the highest precision and can well estimate the values of white noise.

6. Conclusion

This paper presents a new particle filter algorithm based on clone particle swarm which can enhance the convergence speed and grantee the population diversity while enlarge the local searching range, thereby improving the quality of the particles. The experiment results indicate that the algorithm in this paper conduces to enhancement of particle filter precision and speed as well as good robust, thus it is of great application value in practical engineering.

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References

Jianliang Zhu received Master’s degree from Nanjing University of Science and Technology in 2007, and the PhD degree in automation from Nanjing University of Science and Technology in 2012. He is currently a supervisor of master students in Nanjing University of Science and Technology. His research interests are in the areas of Control theory and control applications, information processing, intelligent optimization algorithm and information systems.