Blind separation of PCMA signals based on improved particle filter algorithm

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Abstract. For the problem of particle degradation and depletion in the blind separation of particle filter algorithm, particle swarm optimization algorithm and genetic algorithm are used to improve the traditional PCMA blind separation algorithm based on particle filter. The improved algorithm uses particle swarm optimization algorithm to optimize the particle and uses genetic algorithm to resample the particle. It can maintain the diversity of particles and reduce the problem of particle degradation and dilution effectively. The simulation shows that the improved blind separation algorithm has better separation performance.

1 Introduction

The PCMA signal belongs to a single channel co-frequency signal, so the blind separation of PCMA signals belongs to the category of single channel co-frequency signal blind separation. The particle filter algorithm belongs to Monte Carlo method based on Bayesian estimation, which can be used for filtering problems of nonlinear and non-Gaussian systems. In [1], particle filter algorithm is used to solve the problem of single channel co-frequency signal blind separation.

However, as the number of iterations increases, the algorithm has the problem of particle degradation and dilution, and the blind separation performance is not good under the condition of low SNR. In this paper, a blind separation algorithm based on improved particle filter is proposed to solve the problem of particle degradation and dilution. The improved algorithm applies particle swarm optimization and genetic algorithm to traditional particle filter algorithm. Firstly, the particle swarm optimization is performed on the sampled particles. When a certain condition is met, the genetic algorithm is used for resampling, and finally the traditional particle filter blind separation algorithm is realized. This paper mainly introduces the improved particle filtering method, and only describes the traditional particle filtering method briefly.

2 Principle of particle filter

In digital communication systems, the mathematical model of PCMA is:

\[ y(t) = h_1 e^{j(\Delta \omega t + \theta_1)} \sum_{n=-L}^{L} s_n^{(1)} g_1(t - nT + \tau_1(t)) + h_2 e^{j(\Delta \omega t + \theta_2)} \sum_{n=-L}^{L} s_n^{(2)} g_2(t - nT + \tau_2(t)) + v(t) \]  

(1)

Where, \( h_1, \Delta \omega, \theta_1, \tau_i(t) (i=1,2) \) are amplitude, frequency offset, phase offset and delay of component signals respectively. \( g_i \) is the baseband equivalent filter, which can be expressed as:
\( g_i(t) = \frac{\sin(\pi t / T) \cos(\alpha_i \pi t / T)}{\pi t / T} \left(1 - 4\alpha_i^2/t^2 \right) (0 < \alpha_i < 1) \)  

(2)

The particle filter algorithm establishes the state space model by using the symbol sequence and modulation parameters of component signals as state variables. By introducing the importance function, the posterior probability distribution of symbol sequence is solved, then the blind separation of PCMA signals is finally realized. The weight of importance can be described as

\[
0:1 \pi \pm \pi \cdots 0:1
\]

\[
p_i(y_{\mathbf{d}} | y_{\mathbf{d}-1}, z_{\mathbf{d}-1}) p(z_{\mathbf{d}} | y_{\mathbf{d}}, z_{\mathbf{d}-1}) \]

\[
\prod_i \left( z_{i,D} | z_{i,D-1}, y_{0:K} \right)
\]

After the importance weight is obtained, the signal parameters can be estimated using LMMSE:

\[
\theta_{\text{LMMSE}} = \sum_{i=1}^{N} w_i \hat{\theta}_i
\]

(4)

MAP is used to estimate the symbol sequence:

\[
\phi_{\text{MAP}} = \arg \max_{\mathbf{\phi}_{D-D}} \left\{ \sum_{i=1}^{N} w_i \delta \left( \phi_{D-D} - \phi_{i,D} \right) \right\}
\]

(5)

3 Improved particle filter algorithm principle

3.1 Optimization of particle filter by PSO algorithm

In the particle swarm optimization algorithm, it is assumed that there is an m-dimensional target search space, and there are populations with n number of particles \( X = (X_1, X_2, \ldots, X_n) \). Set the position of the ith particle to \( x_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,m}) \), and the speed of the ith particle to \( v_i = (v_{i,1}, v_{i,2}, \ldots, v_{i,m}) \), \( P_i \) is the current optimal position of the ith particle, \( P_g \) is the global optimal position of the ith particle.

The update formula for particle velocity \( v_{i,d} \) and position \( x_{i,d} \) is as follows:

\[
v_{i,d}^{k+1} = w v_{i,d}^{k} + c_1 r_1 \left( P_{i,d} - x_{i,d}^{k} \right) + c_2 r_2 \left( P_g - x_{i,d}^{k} \right)
\]

(6)

\[
x_{i,d}^{k+1} = x_{i,d}^{k} + v_{i,d}^{k+1}
\]

(7)

Where, \( d \in m \), \( w \) is the inertial weight coefficient, \( c_1 \) and \( c_2 \) are acceleration factors, \( r_1 \) and \( r_2 \) are random numbers in [0,1], \( k \) is the number of iterations.

After optimizing the sampled particles by particle swarm optimization, the particle distribution is closer to the real state, and the particle set can move faster toward the maximum posterior probability. At the same time, the particle weight and the number of effective particles increased. The elimination rate of small weight particles decreased and the diversity of particles was preserved, which alleviated the degradation and dilution of particles effectively.

3.2 Optimization of particle filter by genetic algorithm

Although the particle swarm optimization algorithm can alleviate the problem of particle degradation and depletion effectively, it has small search range and with the increase of iteration times, it is easy to fall into local optimal value. As an intelligent optimization algorithm, genetic algorithm is suitable for global optimization of random search. In addition, genetic algorithms can preserve high-quality particles and protect particle diversity through a series of operations such as selection, crossover, and mutation. Therefore, genetic algorithm can be used to optimize particle filtering.

For particle degradation and particle depletion, genetic algorithm can be introduced to resample particles to ensure particle diversity, so as to reduce the number of sampling particles needed by traditional algorithm effectively.

The genetic algorithm resampling process is as follows:

(1) Selection

Before performing the particle selection operation, it is necessary to calculate the individual fitness function value. Normalize all particle weights and use the weight of the particles as a fitness function,
Calculate the number of effective particles $N_{\text{eff}}$, where

$$N_{\text{eff}} = \frac{1}{N} \sum_{i=1}^{N} (\bar{w}_{k}^{i})^{2}$$

Sort the particle fitness from large to small, select the first $N_{\text{eff}}$ particles for the next operation;

(2) Crossover
Choose any two of the $N_{\text{eff}}$ particles from the selection process to cross and get the corresponding offspring particles.

$$x_{k}^{m'} = P_{x} x_{k}^{m} + (1 - P_{x}) x_{k}^{n}$$

$$x_{k}^{n'} = P_{x} x_{k}^{n} + (1 - P_{x}) x_{k}^{m}$$

Where, $P_{x}$ is the cross factor, $x_{k}^{m}$ and $x_{k}^{n}$ are two parent particles randomly generated by the system at time $k$, the parent particles $x_{k}^{m}$ and $x_{k}^{n}$ are crossed to obtain the child particles $x_{k}^{m'}$ and $x_{k}^{n'}$ to obtain the particle set $\text{pop}_1$.

(3) Mutation
Selecting $N_{\text{eff}}$ particles for mutation in the particle set $\text{pop}_1$ according to the gambling wheel selection operator, and the mutation process is performed according to the formula (12):

$$x_{k}^{m'} = C_{k|k-1} x_{k}^{m} + \epsilon$$

Where, $C_{k|k-1}$ is a first-order Markov chain transfer matrix, $\epsilon \sim N(0,1)$, the particle set is $\text{pop}_2$.

(4) Calculation of the acceptance rate of Metropolis-Hastings:

$$\eta = \frac{P(X_{k}^{m'}, Z_{k}) q(X_{k}^{m'}, X_{k}^{m})}{P(X_{k}^{m}, Z_{k}) q(X_{k}^{m}, X_{k}^{m'})}$$

Set threshold $\mu \sim [0,1]$, if $\mu \leq \min(1, \eta)$, we accept the mutated particles as a sample. According to this, the qualified particles $N - N_{\text{eff}}$ are obtained from the particle set $\text{pop}_2$. The $N - N_{\text{eff}}$ new particles and $N_{\text{eff}}$ particles are combined into a new population, and then the iterative process of the genetic algorithm is performed until the end of the resampling process.

3.3 Blind separation algorithm based on improved particle filter

By analyzing the principles of particle swarm optimization and genetic algorithm, we can find that both algorithms have certain deficiencies. Although the particle swarm optimization algorithm is simple to use and it has a faster convergence speed in the early stage, local convergence is easy to occur in late stage. Genetic algorithm has strong global search ability, but it is difficult to obtain high convergence precision. Therefore, the two algorithms can be combined to optimize the single channel blind separation algorithm of particle filter.

The basic idea of the joint optimization algorithm is to optimize particles by particle swarm optimization algorithm firstly, then update the weight and estimate the parameter and symbol sequence according to the particle filtering method. If the effective particle number is less than the threshold $N_{\text{eff}}$, the particles are sorted according to the importance weight, and the first $N_{\text{eff}}$ particles are selected for the genetic algorithm resampling. Finally, the estimation of the PCMA symbol sequence is realized.

The specific steps of the improved particle blind separation algorithm are as follows:
(1) Initialization: initialize particles based on known prior probability density functions \( p(x_0) \), initialize particles \( x_0^i \), \( i=1,2,\ldots,N, w_k^{(i)} = 1/N \);

(2) Importance sampling: set \( k = k+1 \), accordiing to the importance sampling function \( \pi(z_k^i|z_{k-1}^i, y_{k-1}) \) and particle \( z_k^i \), the new particle \( z_k^i \) is updated;

(3) Weight update: The weights \( w_k^{(i)} \) are updated according to \( w_k^{(i)} \propto w_k^{(i)} p(y_k | z_k^{(i)}) \), and then the weights are normalized according to \( \tilde{w}_k^{(i)} = w_k^{(i)} / \sum_{i=1}^{N} w_k^{(i)} \).

(4) Using PSO optimization algorithm to update the particles: update the position and velocity of the particles according to formulas (6) and (7), update and normalize the weights;

(5) Calculate the number of effective particles \( N_{eff} \), where \( N_{eff} = 1/\sum_{i=1}^{N} (\tilde{w}_k^{(i)})^2 \);

(6) If \( N_{eff} \leq N/2 \), the genetic algorithm is used for resampling, and the particle weight is updated according to \( w_k^{(i)} = 1/N \);

(7) Parameter and symbol estimation: According to formulas (4) and (5), the parameters and symbol estimation of the current sampling time are obtained. Then the parameters and particle symbols of the next sampling time can be predicted by the state transfer equation;

(8) Then go to step (2) to perform an iterative operation until all symbol sequences are output, and the program ends.

4 Simulation Results and Analysis

This experiment uses two QPSK modulated co-frequency mixed signals for simulation. Set the amplitude of the two QPSK signals \( h_1 = h_2 = 1 \), the initial phase \( \theta_1 = \pi/6 \), \( \theta_2 = \pi/3 \), the frequency offset \( \Delta \omega_1 = 200Hz \), \( \Delta \omega_2 = -200Hz \), the delay of the two signals \( \Delta \tau_1 = 0.1T \), \( \Delta \tau_2 = 0.3T \). In this simulation, a raised cosine-forming filter is used as the equivalent filter, and the roll-off coefficient is set to 0.3, the particle smoothness degree \( D = 3 \), and the filter tailing \( L = 2 \).

Firstly, the improved algorithm is used to estimate the parameters of PCMA signals. Figure 1 and figure 2 are simulations of the phase offset, frequency offset of PCMA signals with a particle number of 100 and SNR of 14 dB. It can be seen from the analysis of the simulation diagram that the improved particle filtering method can effectively estimate the parameters of the component signals, which proves the effectiveness and feasibility of the improved algorithm.

![Fig.1. phase offset estimation](image1)

![Fig.2. frequency offset estimation](image2)

In order to verify the blind separation performance of the improved algorithm for PCMA signals, the traditional particle filter blind separation algorithm is compared with the improved blind separation
algorithm, and the error rate of symbol sequence after blind separation is simulated. Figure 3 is a comparison of the improved algorithm with the Ghirmai \cite{3} algorithm and the traditional PF algorithm for blind separation performance when the sampled particle is 500.

![Fig.3. Algorithm performance comparison](image)

It can be seen from the simulation that all the three algorithms have better separation performance, and as the signal-to-noise ratio increases, the bit error rate of the symbol sequence gradually decreases. Also, it can be concluded that the improved particle filter algorithm has better blind separation performance than the traditional particle filter separation algorithm. The improved blind separation algorithm alleviates the problem of particle degradation and particle depletion effectively, and improves the blind separation performance of the particle filter algorithm at the same time.

5 Conclusion

In the paper, an improved algorithm based on particle swarm optimization and genetic algorithm optimization is proposed to solve the problem of particle degradation and depletion in the blind separation of particle filter algorithm. By introducing particle swarm optimization algorithm, the number of effective particles in the operation process is improved, and the number of required particles is reduced. By using particle swarm optimization algorithm, the number of effective particles in operation process is increased, the number of required particles is reduced, and the diversity of the particles is ensured. In view of the shortcomings of the particle swarm algorithm, the genetic algorithm is used to resample the high quality particles and ensure the diversity of the particles, and further solves the problem of particle degradation and depletion in the traditional particle filter algorithm. Simulation experiments show that the improved algorithm improves the blind separation performance of the PCMA signal effectively.

References

[1] K. Liu, H. Li, X.C. Dai, X. Xu. Single Channel Blind Signal Separation of Cofrequency MPSK Signals[C]. Proceedings of International Conference on Communication, Internet and information technology(CIIT 2006), St. Thomas, 2006:42-46.

[2] W. Lu, B. Zhang and X. Lu. Single-channel blind separation of MPSK and LFM interference using genetic particle filtering[C]. 2013 IEEE Third International Conference on Information Science and Technology (ICIST), Yangzhou, 2013:1460-1464.

[3] Tadesse Ghirmai, Monica F. Bugallo, Joaquin Miguez, et al. A Sequential Monte Carlo Method for Adaptive Blind Timing Estimation and Data Detection[J]. IEEE Transactions on Signal Processing: A publication of the IEEE Signal Processing Society, 2005, 53(8):2855-2865.