Separating for Nonlinear Mixed Rotor Fault Signals Based on Adaptive Particle Swarm Optimization

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Abstract. The performance of existing nonlinear mechanical failure signal separation methods is affected by the non-linear contrast function that is selected according to the distribution of original signals. To solve this problem, a blind source separation algorithm based on adaptive particle swarm optimization is proposed, which takes the negentropy of mixtures as a contrast function. The inertia weight factor depends on the negentropy, which can improve the contradiction between the convergence speed and the performance of separated signals. The simulation results verified the effectiveness of the proposed method. Finally, some mixed rotor vibration signals were separated successfully using the proposed method.

1. Introduction

Blind source separation (BSS) technology is a new method developed in the 1980s. It is a process based on the statistical characteristics of the source signal. Only the observed mixed signal returns the unknown source signal. It is an artificial neural network, statistical signal processing and information theory combined with the method [1]. At present, many different algorithms have been developed. These algorithms involve the selection of nonlinear functions, but the choice of function model depends on the probability density property of the signal source [2-6]. In practical applications, the probability density of the source signal is generally unknown before the signal is separated, especially for the super-Gaussian signal and the sub-Gaussian mixed signal, the separation ability of the blind separation algorithm often depends on the selection of the nonlinear function [7,8]. In the rotating mechanical vibration test, the signal transmission is often affected by the complexity of the internal structure of the system and the transmission process and other factors, in its existence there are more complex nonlinear process, seriously affecting the accuracy and reliability of mechanical fault diagnosis, different separation algorithms will produce different separation effects [9].

Aiming at this problem, a method of mechanical fault feature extraction based on adaptive particle swarm optimization is proposed. In this method, the negative entropy of the observed signal is chosen as the objective function, and the inertia factor can be adjusted adaptively by observing the state of the signal, which can effectively overcome the contradiction between the signal recovery quality and the convergence speed. Through the separation of the simulation signal, the separation of the output signal and the simulation signal consistency. Finally, the fault signal separation is successfully realized by the method, and the effectiveness of the proposed method is verified.
2. Blind source signal separation

The blind source separation problem refers to the process of recovering individual components only by observing signals without knowing the parameters of the source signal and the transmission channel. The hybrid model is expressed as [1]:

\[ y(t) = As(t) + n(t) \]  \hspace{1cm} (1)

Where \( y(t) = [y_1(t), y_2(t), ..., y_M(t)]^T \) is a N-dimensional random observation vector in the presence of noise, \( A \) is a hybrid matrix of an unknown full rank \( M \times N \), \( s(t) = [s_1(t), s_2(t), ..., s_N(t)]^T \) is an M-dimensional source signal, and each component \( s_i(t) \) in the source signal is assumed to be statistically independent and contains up to A Gaussian noise, otherwise not be separated; \( n(t) = [n_1(t), n_2(t), ..., n_M(t)]^T \) is a M-dimensional noise signal.

3. Blind Source Separation Algorithm Based on APSO

The particle swarm optimization algorithm was first proposed by Dr. Eberhart and Dr. Kennedy in Ref. [5], which was a group-based optimization tool with global optimization capabilities. Suppose that in a D-dimensional search space there are N random particles, where the position of each particle represents a potential solution. Particles in the iterative process, by tracking two extreme values to adjust themselves: the first is the particle itself to find the optimal solution, known as the individual extreme \( P \), can also be seen as the flight experience of particles; the other extreme is all Particle group to find the optimal solution, known as the global extreme value \( G \), also known as group experience.

The Particle swarm optimization algorithm is manipulated using the following formula:

\[ v^{i+1}_j = v^i_j + c_1 r_1 (p^i_j - x^i_j) + c_2 r_2 (g^i_j - x^i_j) \]  \hspace{1cm} (2)

\[ x^{i+1}_j = x^i_j + v^{i+1}_j \]  \hspace{1cm} (3)

Where \( t \) is the current number of iterations; \( c_1, c_2 \) is the learning factor and is the normal number used to adjust the traction between the optimal position and the global optimal position. \( r_1, r_2 \) is a random number between \([0,1]\);

Where the independence of the signal is chosen from the negative entropy to measure, Comon [1] proves that the negative entropy of the multivariate can be expressed as

\[ J_y(y_i) = \frac{1}{12} k_3^2(y_i) + \frac{1}{48} k_4^2(y_i) + \frac{7}{48} k_4^4(y_i) - \frac{1}{8} k_2^2(y_i) k_4(y_i) \]  \hspace{1cm} (4)

Where \( k_3(y_i) \) is the third-order cumulant; \( k_4(y_i) \) is the fourth-order cumulant. If the sampling signal signal distribution is symmetrical probability distribution, then \( k_3 = 0 \), then

\[ J_y(y_i) = \frac{1}{48} k_4^2(y_i) \]  \hspace{1cm} (5)

The fourth-order cumulant \( k_4(i) \) is normalized to

\[ k_4(y_i) = \frac{E(y_i^4)}{E(y_i^2)^2} - 3 \]  \hspace{1cm} (6)

\( k_4(y_i) \) is the kurtosis of the signal; \( k_4(y_i) = 0 \) signal is a gaussian signal; \( k_4(y_i) < 0 \) signal is owed gaussian signal; \( k_4(y_i) > 0 \) signal is a super gaussian signal; Because \( k_4(y_i) > 0 \), the bigger \( k_4^2(y_i) \), the stronger the non-gauss.

In this paper, the negative entropy of the sampled signal is used as the objective function of the particle swarm optimization algorithm.
Under the constraints of $E(xx^T) = I$, for the separation matrix $W$, the larger $f(y)$, the greater the independence of the separation signal, the better the source separation effect.

The number of particles is $n$, the fitness of the optimal particles is $f_{\text{max}}$, and the fitness of the particles $f_i$ in the iteration is $f_i$. The average fitness of the particle group is $\overline{f} = \frac{1}{n} \sum_{i=1}^{n} f_i$, and the fitness of the particle that is better than $\overline{f}$ is equal to $\overline{f}$, the inertia factor can be adjusted by $f_i$ and $f_{\text{max}}$. The formula is [8]

$$w = w_0 \exp\left(-a \cdot \frac{f_i}{f_{\text{max}}}\right)$$

In the formula, the selection of $a$ and $w_0$ has a great influence on the performance of the algorithm. If $a$ is too small, the adjustment ability of equation (8) is insufficient; if $a$ is too large, the algorithm is easy to fall into local optimum.

In summary, APSO-based blind source separation algorithm can be described as:

1) Whitening and centralizing the sampled signal;
2) initialize, set the learning factor $c_1, c_2$, and $w_0, a$, randomly generate a certain number of separation matrix as the initial particles, and randomly generate the particle movement speed;
3) Push $Y$ according to the separation formula $Y = WX$, and center and whiten the $Y$, and push the adaptive value of the particle by the objective function.
4) Update the individual optimal $p_i$ of each particle and the global optimal $g_i$ of the whole population; then update the position and velocity of the particle according to (3) and (4).
5) To determine whether to meet the termination conditions. If it is satisfied, go to step 6); otherwise, go to step 3) and continue iterating.
6) Output the final global optimal $g_i$, the algorithm is running.

4. Simulation research and analysis

4.1. Evaluation Criteria

In order to evaluate the effect of signal separation effectively, the similarity coefficient is used as the evaluation index of the difference between the separation signal and the source signal. The similarity coefficient is defined as:

$$\xi_y = \xi(y_i, s_j) = \frac{\sum_{t=1}^{M} y_i(t)s_j(t)}{\sqrt{\sum_{t=1}^{M} y_i^2(t)\sum_{t=1}^{M} s_j^2(t)}}$$

In the formula, when $\xi_y$ is constant, that is, the separation of the signal amplitude difference; when the separation signal and the source signal is independent of each other, $\xi_y$. It is also said that if the similarity coefficient matrix is equal to 1 for each row and each column and only one element is close to zero, then the separation effect of the algorithm is considered to be ideal.

4.2. Simulation

I Rotor in the presence of rubbing, cracks, not the middle of the fault, the sensor is often the signal collected aliasing fault signal and AM FM signal. Simulation test in the choice of four kinds of signals, sampling length of 1024, the source signal production function is as follows:
\[ s(t) = \begin{bmatrix} s_1(t) \\ s_2(t) \\ s_3(t) \\ s_4(t) \end{bmatrix} = \begin{bmatrix} n(t) \\ 3\sin 0.4t \cos 10t \\ \sin 3t + \sin 6t + \sin 10t \\ \sin 2t \end{bmatrix} \]

Source signal \( s_1(t) \) analog noise signal, \( s_2(t) \) simulation frictional fault characteristic signal, \( s_3(t) \) simulation misalignment fault characteristic signal, \( s_4(t) \) analog period vibration signal; \( s_1(t), s_2(t), s_3(t), s_4(t) \) time domain waveform shown in Figure 1. The source signal is generated by random mixing of the observed signal \( x_1(t), x_2(t), x_3(t), x_4(t) \), the mixing mode is linear superposition, and the time domain waveform of the mixed signal is shown in Fig.

In the simulation experiment, the particle swarm optimization algorithm and the adaptive particle swarm optimization algorithm are used to separate the mixed signal, and the separation signals are shown in Fig. 3 and Fig.

[Fig. 1 The simulative signal](image1)

[Fig. 2 The mixture of simulative signal](image2)

[Fig. 3 The separated signal using PSO](image3)

[Fig. 4 The separated signal using APSO](image4)

Compared with Fig. 3 and Fig. 4, it can be seen that the source signal separated by the general particle swarm algorithm does not reflect the source signal well. The improved adaptive particle swarm optimization algorithm reflects the waveform information of the source signal well. Although the source signal and the separation signal in the amplitude and order there is inconsistent, but does not affect the identification of signal characteristics. The simulation results show that the adaptive particle swarm optimization algorithm is used to quantify the similarity between the signal and the source signal. The similarity coefficient matrix:

\[
\xi = \begin{bmatrix} 0.0001 & 0.0214 & 0.0051 & 0.9997 \\ 0.0031 & 0.0572 & 0.9996 & 0.0327 \\ 0.0861 & 1.0000 & 0.0008 & 0.0141 \\ 1.0000 & 0.0013 & 0.0012 & 0.0069 \end{bmatrix}
\]

The underline factor is expressed as the correlation coefficient between the separation signal and
the source signal. It can be seen from $\xi$ that the similarity coefficient of the separation signal and the source signal based on the particle swarm optimization algorithm is very high, which shows that the improved adaptive particle swarm optimization algorithm can accurately extract the source signal characteristics from the mixed signal.

5. Analysis of actual rotor vibration signal
In order to verify the separation performance of the above algorithm to the measured aliasing vibration signal, the vibration signal of the measured aliasing rotor is analyzed in this paper. As the rotor in the rotation process, there may be a number of potential source signals, such as the bearing ball vibration signal, the axis of the axial vibration signal and noise signals, and the sensor is measured at the same time, so the sensor measured signal is aliasing vibration signal. In order to meet the assumption that the number of sensors in the blind source separation is greater than or equal to the number of source signals, four sensors are used for the measurement. Rotor in the rotation process speed is about 2800 r/min, sampling frequency of 5000Hz. The time domain signal after direct separation by the APSO algorithm is shown in Fig.7. In order to compare the complex vibrations of the rotor before and after the separation, the data of the data signals before and after the separation are analyzed, and the different characteristics of the signal before and after the separation are observed from the frequency domain. The spectrum before and after separation is shown in Fig. 6 and Fig.8.

![Fig. 5 The vibration signal for rotor with multi-faults](image1)

![Fig.6 FFT of vibration signal for rotor with multi-faults](image2)

![Fig.7 The separated signal using APSO](image3)

![Fig. 8 FFT of the separated signal using APSO](image4)

It can be seen from Figure 6, the rotor rotation frequency and its frequency $2 \times, 3 \times$ and other frequency characteristics in the order spectrum is more obvious, you can see the fault signal is aliased together. However, it can be seen from the order spectrum of Fig. 8 that only the $1 \times$ spectral peak is very obvious in the first graph, and the unequal frequency division is shown in the second graph. As
can be seen in the third graph, there are 1 × and 2 × spectral peak, and the 2 × spectral peak is obviously stronger than the 1 × spectral peak, showing the rubbing characteristics; the fourth graph in the time domain shows randomness, you can determine the signal as a noise signal. The above analysis shows that the APSO algorithm can get a better separation effect under the condition of unbalanced - rub - impact - misalignment.

6. Conclusions
The simulation results show that: 1) The established blind source separation algorithm based on adaptive particle swarm optimization is needed to select the nonlinear function by observing the signal state adaptively. Adjust the inertia factor, effectively overcome the signal recovery quality and convergence speed between the spear. 2) The results of numerical simulation show that the source signal can be effectively separated based on the adaptive particle swarm optimization and has high stability. 3) The separation of the fault signal in the case of unbalanced - rub - impact - misalignment is achieved, and a good separation effect is obtained. It is feasible to isolate the rotor fault signal separation method.

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