Study of blind source separation algorithm based on particle swarm optimization in nuclear power background

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Abstract: In nuclear power plant or marine nuclear power plant, mechanical devices that carry the important functions such as power transmission tends to age due to high-speed operation of components. If they cause a malfunction, it will have serious consequences. However, these devices and components usually generate vibration during operation, and there is often a close relationship between the signals generated by the vibration and the operating conditions. The effective monitoring and analysis of the relevant vibration signals enables the timely detection and elimination of equipment failures and other factors that endanger safety, then we can ensure the normal operation of equipment and facilities. The vibration signal measured in reality is a complex mixed signal from multiple unknown vibration sources, and sources of vibration signals need to be differentiated before signal analysis. In this context, blind source separation can be used. Simulation results show that the blind source separation algorithm based on particle swarm optimization can effectively separate signals, the convergence speed of the algorithm is fast. After adding the gradient information to optimize, the convergence speed slightly improves.

Keyword: blind source separation; particle swarm optimization; gradient acceleration

1 Introduction

The ecological deterioration caused by the economic development has made the world's demands for energy conservation and emission reduction more urgent. Nuclear energy, one of the most efficient clean energy sources, which is increasingly used in nuclear power plants and ship nuclear power applications under the requirements of low-carbon development. However, nuclear fuel is radioactive. Once a nuclear leak is caused due to mechanical equipment failures in nuclear facilities, it will cause even more severe human and ecological impacts. The Fukushima nuclear accident and the Chernobyl accident that caused serious negative impact on the history of nuclear energy have confirmed this view at an incalculable price.

In order to realize the goal of nuclear safety, during the operation of nuclear equipment, it is necessary to track and analyze its operating status, so as to discover potential threats in time and avoid accidents. Many important nuclear devices usually contain rotating machinery. The abnormal state of the machine can change the vibration signal during operation. Therefore, the abnormal state of operation can be analyzed by observing the vibration signals of these devices [2]. However, due to the influence of the environment and acquisition equipment, the actual collected observation signals are usually complex signals obtained by mixing multiple signal sources through unknown methods. Such mixed signals cannot directly contribute to equipment fault diagnosis[3]. In this context, studying the source signal extraction and separation technology of nuclear equipment vibration is of great significance to nuclear equipment fault diagnosis and nuclear safety culture.

2 Blind Source Separation

The Blind Source Separation (BSS) algorithm is an effective method to separate the source signal from the monitored mixed signal according to certain conditions and assumptions in the case that the mixing method between the source signal and the signal is not known[4]. This method can be applied in nuclear equipment fault diagnosis technology. It is necessary

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to select an appropriate independence criterion as an indicator of the degree of independence of blind source separation results, such as a non-Gaussian criterion[5]. Kurtosis is often used as a non-Gaussian measure. The kurtosis of a zero-mean real signal y is its fourth-order cumulant, defined as:

$$kurt(y) = \mathrm{E}\left(y^4\right) - 3\mathrm{E}^2\left(y^2\right) \tag{1}$$

Normalize the formula above, then

$$kurt(y) = \mathrm{E}\left(y^4\right) / \mathrm{E}^2\left(y^2\right) - 3 \tag{2}$$

When the variance of the signal is 1, the above equation can be written as

$$kurt(y) = \mathrm{E}\left(y^4\right) - 3 \tag{3}$$

The formula shows that the kurtosis can be converted into a standard fourth-order moment and the fourth-order moment of the Gaussian distribution signal is $3\mathrm{E}^2\left(y^2\right)$, so its kurtosis is zero. Therefore, when kurtosis is equal to zero, y is a Gaussian distribution; when kurtosis is positive, y is a super-Gaussian distribution; when the kurtosis value is a negative value, y is a sub-Gaussian distribution. There is a positive correlation between the absolute value of kurtosis and the non-Gaussian of y. Therefore, the problem of blind source separation of observation signals can be transformed into the problem of solving the absolute value or square maximum of the observed signal kurtosis. If the maximum value can be found, it means that the separation of the observation signal is effective[6].

Many existing blind source separation algorithms use independent component analysis (ICA) methods[7-8]. In order to ensure that the basic ICA model can be estimated, it is necessary to set the following assumptions and constraints: each component is statistically independent; independent components must have a non-Gaussian distribution; the number of independent components is equal to the number of observed mixed signals; mixing matrix is reversible.

To establish an ICA model, the objective function is usually selected first according to the independence criterion, then minimize or maximize the objective function. So the nature of the ICA method depends on the objective function and the optimization algorithm, and the optimization algorithm determines the performance of the blind source separation algorithm such as convergence speed and separation effect to a large extent.

3 Particle Swarm Optimization algorithm and its improvement

3.1 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a kind of optimization computing technology and it is an intelligent algorithm developed by simulating bird foraging behavior[9]. Particle swarm optimization algorithm is determined by less empirical parameters and is easy to control. And because of its theoretical parallelism, the convergence speed is very fast, so it has been well promoted.

The initial particle of the standard PSO algorithm is a set of particles with random velocity and location. Each particle continuously flies within the search space and finds the optimal solution through iterative methods. During iteration, the particle is continuously updated according to the two "extreme values", constantly adjusting its position. The first extremum is called the individual extremum and is the optimal solution found by the particle itself. The individual extremum of the i-th particle is denoted as $P_i = [p_{i1}, p_{i2}, \cdots, p_{id}]$. The second extremum is called the global extremum. It is the optimal solution that the current population can find, denoted as $P_g = [p_{g1}, p_{g2}, \cdots, p_{gd}]$. When these two optimal solutions are found, the particles update their position and velocity according to:

$$\begin{aligned} v_{ij}(t+1) &= wv_{ij}(t) \\ &\quad + c_1 r_1[(p_{ij})_j(t) - x_{ij}(t)] \\ &\quad + c_2 r_2[p_{gj} - x_{ij}(t)] \\ x_{ij}(t+1) &= x_{ij}(t) + v_{ij}(t+1) \\ &\quad 1 \le i \le n, 1 \le j \le d \end{aligned} \tag{4}$$

Where c_1 and c_2 are positive constants called acceleration factors; r_1 and r_2 are random numbers between [0, 1]; w is called the inertia weight; the j-dimension $(1 \le j \le d)$ of the position change range is $[-x_{j,\max}, x_{j,\max}]$, and the speed range is $[-v_{j,\max}, v_{j,\max}]$. During iteration, if a x_{ij} or v_{ij} value in a certain dimension crosses the boundary, its value is set as the boundary value. At the beginning of the algorithm, the initial position and velocity of the particle swarm are randomly generated. Before the stop condition is satisfied, the iteration is continued through equation (4). The universal adaptability of the standard PSO algorithm is a big advantage, but the algorithm lacks consideration of the special nature of the particular problem, and useful information such as gradients is often overlooked. And the standard PSO algorithm does not dynamically adjust the speed, resulting in weaker particle climbing ability, which leads to the late iteration performance of the algorithm significantly worse than the early performance [10].

3.2 gradient-accelerated PSO algorithm

In order to solve the above problem, it is possible to properly inject some gradient information in the process of the particle speed iteration update, which helps the particles to make highly targeted and more efficient movements.

The gradient representation of the function $f(\boldsymbol{x})$, $\boldsymbol{x}=(x_1,x_2,\cdots,x_n)$ is:

$$\nabla f(\boldsymbol{x})=[\frac{\partial f(\boldsymbol{x})}{\partial x_1},\frac{\partial f(\boldsymbol{x})}{\partial x_2},\cdots,\frac{\partial f(\boldsymbol{x})}{\partial x_n}]^T \tag{5}$$

Each time the particle updates its velocity and position, it completes the iteration according to equation (4) with the probability p, completes the iteration according to gradient information with the probability of $(1-p)$, and completes the update with a certain step length in the direction of the negative gradient.

Adding gradient information can improve the convergence speed of the algorithm, but for some specific problems, adding gradient information makes it easier for particles to fall into the local optimal solution. Therefore, when considering gradient acceleration, it is necessary to debug the influence of gradient information on particle movement according to the characteristics of the problem.

4 Simulation experiments and results

In order to verify intuitively whether the above algorithm can achieve the desired effect, simulation experiments were conducted on the problem of mixed signal separation. In the experiment, standard signals were used to simulate the source signals, these signals were linearly mixed, and the resulting mixed signals to be separated and simulated the actual observation signals. The standard signals used in the experiment were:

Sinusoidal signal： $s_1=2*sin(0.02*pi*n)$;

Square wave signal： $t=1:N$;

$s_2=2*square(100*t,50)$;

Sawtooth signal： $a=linspace(1,-1,25)$;

$s_3=2*[a,a,a,a,a,a,a,a]$;

Random noise： $s_4=rand(1,N)$;

In order to facilitate the comparison of multiple algorithms, the experimental results must be quantified. In the experiment, the correlation coefficient was used as the evaluation criterion to evaluate the similarity between the separation result and the source signal. Let the i-th source signal in the source signal vector s be s_i. The separated signal corresponding to signal s_i is $\hat{s}_\mathrm{j}$. The correlation coefficient between the two signals is:

$$\rho_{\mathrm{ij}}=\frac{\mathrm{cov}(s_\mathrm{i},\hat{s}_\mathrm{j})}{\sqrt{\mathrm{cov}(s_\mathrm{i},s_\mathrm{i})\,\mathrm{cov}(\hat{s}_\mathrm{j},\hat{s}_\mathrm{j})}} \tag{6}$$

Where $\mathrm{cov}(\cdot)$ is the covariance. According to probability theory statistics knowledge, $|\rho_{\mathrm{ij}}|$ must be less than 1, when $|\rho_{\mathrm{ij}}|$=1, it means that s_i and $\hat{s}_\mathrm{j}$ are exactly the same, and when $|\rho_{\mathrm{ij}}|$=0, it means that the two signals are independent statistics.

In the experiment, the kurtosis is selected for the objective function, and each parameter is selected as follows: Population size is 50; learning factors c_1 and c_2 are 2; the maximum particle speed $v_{\max}$ is 1; the inertia factor uses a Linear Decreasing Weight Strategy (LDW)[11-12], $w_{\min}=0.4$, $w_{\max}=0.9$; the mixing matrix A is a randomly generated square matrix. The results of experiment 1 are shown in Fig.1.

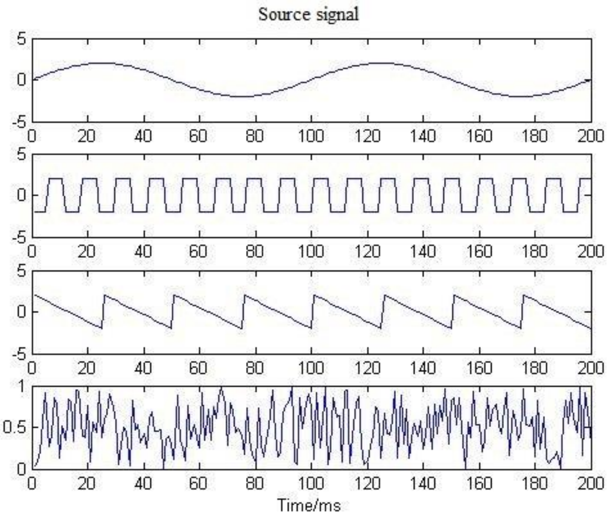

Fig.1 Experiment 1 source signal.

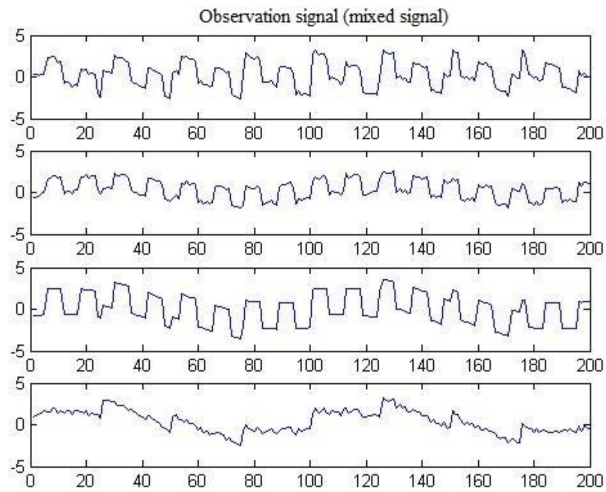

Fig.2 Experiment 1 mixed signal.

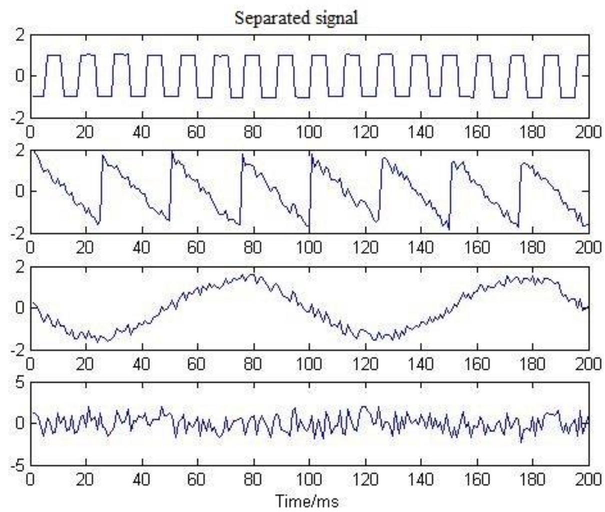

Fig.3 Experiment 1 separated signal.

During the experiment, record the mixing matrix A as follows:

$$A = \begin{pmatrix} 0.049033 & 0.607082 & 0.770814 & 0.579727 \\ 0.423695 & 0.494042 & 0.113714 & 0.657231 \\ 0.608098 & 0.787197 & 0.355118 & 0.072574 \\ 0.810835 & 0.060461 & 0.491043 & 0.759289 \end{pmatrix}$$

The separation signal is shown in Fig.3. The signal waveform can well reflect the information it carries. By comparing Fig.1 and Fig.3, we can see that the separated signal obtained by the algorithm can well restore the source signal. The reduced sinusoidal signal and sawtooth signal are slightly coarser than the source signal, which is caused by errors in the calculation process. In order to evaluate the result, the similarity coefficient between the separated signal and the source signal is calculated. The blind source separation similarity coefficients of the standard PSO algorithm are as follows:

Table 1 Similarity coefficient of experiment 1

	Square wave signal z_1	Sawtooth signal z_2	Sinusodal signal z	Random noise z_4
Sinusoidal signal s_1	0.01514413	0.06494129	**0.98377039**	0.16658060
Square wave signal s_2	**0.99980083**	0.00865633	0.01627993	0.00763698
Sawtooth signal s_3	0.04267100	**0.98346329**	0.03641952	0.17219976
Random noise s_4	0.05264247	0.25034734	0.18525419	**0.94880759**

The separation matrix obtained from the experiment is:

$$W = \begin{pmatrix} 0.016910 & -0.340221 & -0.085743 & -0.936275 \\ -0.301260 & 0.861906 & 0.226261 & -0.339359 \\ 0.496717 & -0.070670 & 0.863886 & -0.044462 \\ 0.813773 & 0.369286 & -0.441761 & -0.079035 \end{pmatrix}$$

In order to study the improved algorithm of the above algorithm, gradient information is introduced based on the standard PSO algorithm. In the experiment, the particles were updated with the probability of 0.1 according to the gradient information and iterated with a probability of 0.9 according to formula (4). In order to better compare the algorithms before and after the optimization, the experimental parameters are consistent with the standard PSO algorithm, and the mixing matrix uses the matrix A recorded in the previous experiment. Therefore, the source signal and the mixed signal of Experiment 2 are the same as Experiment 1, as shown in Fig.1 and Fig.2.

Here only the separation signal of experiment 2 is given. The results of experiment 2 are as follows:

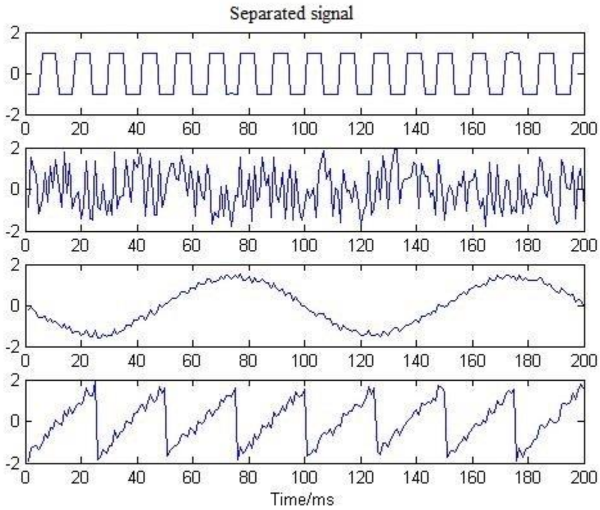

Fig.4 Experiment 2 separated signal.

By observing the waveforms before and after separation, it can be seen that the gradient-accelerated PSO blind source separation algorithm can also achieve the desired target well, and the separation effect is also good. Also due to the influence of the optimization calculation accuracy, the separation signal surface is not as smooth as the source signal. In the calculations, the sawtooth signal reversed phase due to the uncertainty introduced by the mixing matrix. This phenomenon may also occur in the standard PSO. The BSS similarity coefficient of gradient-accelerated PSO algorithm is shown in Table 2:

Table 2 Similarity coefficient of experiment 2

	Square wave signal z_1	Random noise z_4	Sinusodal signal z	Sawtooth signal z_2
Sinusoidal signal s_1	0.00608032	0.09951065	**0.99430779**	0.03758549
Square wave signal s_2	**0.99998767**	0.00355495	0.00309390	0.00156244
Sawtooth signal s_3	0.03379722	0.18853727	0.01843201	**0.98131121**
Random noise s_4	0.05439551	**0.98581258**	0.04212381	0.15310208

The separation matrix obtained from the experiment is:

$$W=\begin{pmatrix} 0.024915 & 0.911651 & 0.199300 & 0.358537 \\ -0.304550 & 0.297893 & 0.243123 & -0.871434 \\ 0.521302 & -0.190139 & 0.831782 & -0.015123 \\ 0.796788 & 0.209754 & -0.457501 & -0.334399 \end{pmatrix}$$

5 Comparison of experimental results

It can be seen from the above two experimental results that the standard PSO blind source separation algorithm and the gradient-accelerated PSO blind source separation algorithm can solve the linear BSS problem well. By comparing the separated signal obtained by the algorithm and the source signal, it can be seen that the waveform can be well separated. Since the waveform contains the main information of the signal, it can be regarded as an excellent algorithm to achieve the goal of blind source separation. In the experiment process, before and after the optimization of the algorithm, some signals randomly appear to be reversed-phase in the separation process. This is due to the fact that matrix A is a randomly generated mixing matrix in the mixing process of the signal and introduces uncertainty into the observed signal. The algorithm cannot effectively recognize this uncertainty during the process. The waveform of the separated signal is not particularly smooth compared to the source signal. This is due to the fact that there are some errors in the particle optimization calculation during the calculation process.

Through the calculation of the program, the correlation coefficients between the four separated signals and the source signals under the two algorithms have been given by the previous text. The magnitude of the obtained correlation coefficient also verifies the conclusion reached through the above waveform diagram. Compare the two algorithms as follows:

Table 3 Comparison of similarity coefficient between experiment 1 and experiment 2

	Sinusoidal signal	Square wave signal	Sawtooth signal	Random noise
standard PSO ρ	0.98377039	0.99980083	0.98346329	0.94880759
gradient-accelerated PSO ρ	0.99430779	0.99998767	0.98131121	0.98581258

From the comparison of waveforms and correlation coefficients, the optimized algorithm has a slightly better separation effect than the standard particle swarm optimization-based BSS algorithm. In terms of the convergence speed of the algorithm, since each experiment has randomness, the closing speed cannot give a definite value, and comparison can be made through the convergence image.

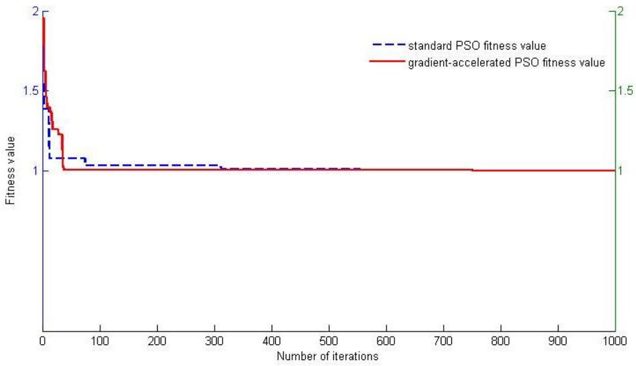

Fig.5 Comparison of the convergence speed between experiment 1 and experiment 2.

From the convergence curve in Fig.5, it can be seen that after adding gradient acceleration information, the convergence speed of the algorithm is also accelerated, but this increase is not significant. This is because the convergence rate of the standard PSO algorithm itself is relatively fast, and the complexity of the linear blind source separation problem is not enough to highlight the advantages of this gradient-accelerated optimization algorithm.

The fast convergence speed is a big advantage of the particle swarm optimization algorithm, but the algorithm also exposes some defects in the running process due to the convergence speed and other factors. In the process of carrying out a large number of repeated experiments, there is no guarantee that each separation is very good and there is a large deviation. This shows that the particles are trapped in the local optimal solution, resulting in failure of the optimization, and in the end, the resulting separation matrix can not achieve the desired effect. Especially when the gradient information is introduced, the convergence rate will further increase, and the problem of falling into the local optimal value will be more easily highlighted. Therefore, in the experiment, the adjustment of the probability p is very important.

6 Conclusion and outlook

The problem of mechanical fault diagnosis for some important nuclear equipment is similar to the problem of blind source separation. Solving the problem of BSS has important significance for nuclear safety culture. In this paper, simulation experiments are carried out to verify the effectiveness of the blind source separation algorithm based on PSO and the optimization algorithm after introducing gradient information to solve the linear blind source separation problem.

From experiments, we can know that the blind source separation algorithm based on particle swarm optimization can solve the linear BSS problem. From the experimental results, it can be seen that the signal after reduction is similar to the standard signal used in the experiment. The similarity coefficient calculated from the experiment also confirms this conclusion. The restored signal image is not as smooth as the standard signal image, which is caused by the limitation of the search accuracy. This phenomenon can be accepted within a certain error range. From the observation, it can be seen that the program can effectively separate the linear mixed signal, and the convergence speed of the algorithm is fast.

The data and figures given in the experiment can show that the optimized algorithm has further improved both in accuracy and convergence speed, which shows that the introduction of gradient information does improve the performance of the algorithm.

There are also other phenomena in the experiment. Although the optimized program has a slight improvement in the convergence speed, in the process of solving random problems, if the gradient information occupies a large proportion, the algorithm is more likely to fall into the local optimal solution; on the contrary, it will not achieve the purpose of optimization. In view of this situation, we can consider introducing new methods to further modify and optimize the program. For example, considering the influence of parameters, we can adjust the learning factor from a constant to a dynamic learning factor, so that the particles can better escape from the local optimum; or in the calculation process, some particles are re-randomly initialized according to appropriate conditions to increase the activity of the particles, so that the particles are more likely to reach the best value.

The algorithm studied in this paper is far from the engineering application. In practice, the mixed signals observed in nuclear power plants or marine nuclear power plants are more complex. Because the signal mixing method is often non-linear, and the complex ambient noise may interfere with valuable signals, the complex blind source separation problem needs to consider more factors for further study.

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