Application of blind source separation to fault diagnosis of nuclear power equipment

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Abstract: Abstract: Nuclear power, which has been developing for 86 years, has become a major clean energy for human. With the development of nuclear power equipment, the requirements for safety and reliability of nuclear power equipment keep increasing. To ensure the safety and stable status of a nuclear power plant, it is necessary to constantly monitor equipment operational condition, timely discover abnormal operation of nuclear power equipment and correctly diagnose the fault of nuclear power equipment. Signal processing, feature extraction, pattern recognition, and decision making are included in Fault diagnosis. The premise and foundation of these four steps is signal processing. In this paper, blind source separation based on artificial bee colony algorithm is applied to the signal processing in order to overcome the complex environment of the nuclear power plant and difficulty in signal extraction. Initialization, update strategy and adjustment strategy of the traditional artificial bee colony algorithm is optimized, and then the convergence speed and stability of the artificial bee colony algorithm are improved. Finally, simulation experiment results show that the algorithm proposed in this paper has better stability, convergence speed and global ergodicity compared with the traditional artificial bee colony algorithm, which also means the algorithm is feasible.

Keyword: fault diagnosis; blind source separation; artificial bee colony

1 Introduction

The application of Blind Source Separation (BSS) algorithm in fault diagnosis is mainly studied in this paper. It aims to separated mixed signals by BSS algorithm based on Artificial Bee Colony (ABC), and optimize the traditional ABC algorithm to improve its stability, convergence speed and separation effect to make it more suitable for signal processing of fault diagnosis. The BSS algorithm was first proposed by Herault and Jutten in 1985: two statistically independent signals from the mixed signal are extracted by search method [1]. Various algorithms were applied to the problem of blind source separation by scholars [2-5]. ABC algorithm was proposed in 1995 [6], and used in blind source separation in 1999 for the first time [7]. Compared with other algorithms, ABC algorithm has the characteristics of less control parameters, faster convergence, more simple calculation, and better applicability than other algorithms [8]. Therefore, the ABC algorithm is selected in this paper and optimized to obtain better, faster and more stable separation results.

The main structure of this paper is as follows: in the second part, the process of fault diagnosis and the overall framework of fault diagnosis are introduced. Principle, optimization and calculation process of BSS algorithm based on ABC optimization are introduced in the third part. In the fourth part, the simulation process and result of the optimization algorithm and the traditional algorithm for the same mixed signal are mainly introduced. The fifth part is the summary and outlook.

2 Fault diagnosis

Actually, signal detection, feature extraction, status recognition and diagnostic decisions are included in fault diagnosis, which is a pattern recognition process. The premise of fault diagnosis is signal detection. In actual nuclear power plants equipment operation signal, interference signal from the adjacent device, environment and system noise are consisted in signals collected by the sensor. The difficulty of feature extraction is mainly caused by interference noise mixing. The judgment and decision-making, the safe

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and stable operation of nuclear power plants are affected by the inaccurate result of fault diagnosis directly. Therefore, appropriate method must be taken to eliminate these noise disturbances. These problems can be solved by BSS algorithm effectively. The overall framework of fault diagnosis based on BSS is shown in Fig.1. In this framework, to deal with the mixed foreign interference noise in the multichannel observation of the machine, the source separation technology is used to eliminate interference signal. Subsequently, with the help of redundancy cancellation-based high-order feature extraction method, "independent" fault features are extracted to achieve accurate identification of failure mode.

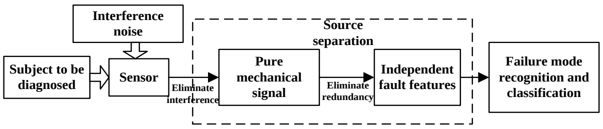

Fig.1 Framework of Fault Diagnosis Based on BSS.

The BSS algorithm based on ABC algorithm will be mainly introduced in this paper.

3 BSS based on optimization ABC algorithm

3.1 Preprocessing of BSS algorithm

In our application, to simplify the BSS algorithm, preprocessing of the received mixed signal before separation is performed, which includes centering and whitening. Prior information is not existed in blind source separation problem. In order to restore the source signal, the following two assumptions are usually made: (1) assume that the signals satisfy statistical independence, (2) the average value of the signal is 0.

It is assumed that the mathematical expectation of the random variable $x(t)$ equals to $E\left[x(t)\right]$, the centralized formula is:

$$\tilde{x}(t) = x(t) - E[x(t)] \tag{1}$$

Assume that the length of the signal is N, the expectation is reduced to the average of the observed data, and the average value is calculated as:

$$E[x(t)] = \frac{1}{N}\sum_{t=0}^{N} x(t) \tag{2}$$

Vector $x(t)$ is the signal after it has been centered. The process of linearly transforming P is called whitening. The mathematical expression is:

$$v(t) = P\tilde{x}(t) \tag{3}$$

$$E\left[v(t)v^T(t)\right] = I \tag{4}$$

It is proved that after the pre-processing, the convergence speed and stability of the algorithm will be improved [9].

3.2 Optimized ABC algorithm

ABC algorithm is a bionic algorithm proposed to simulate the behavior of natural bee colony feeding [10]. In traditional bee colony algorithms, bee colonies are consisted of employment bees, onlooker bees and scout bees. Finding the best quality food source is done by their cooperation. The solution to the problem is the food source sought by bee colonies. The nectar content is corresponding to the fitness of the solution to the problem to be solved. The process of searching and selecting food sources is seen as the process of solving. In this paper, the optimization of ABC algorithm mainly is focused on initial food source, update strategy and adjustment strategy of food source. The flow chart of the optimized ABC algorithm is shown in Fig.2.

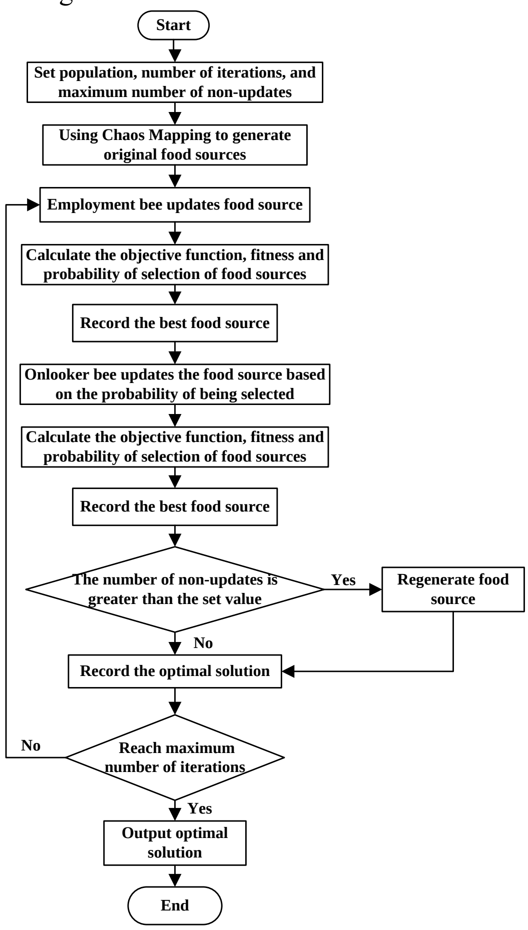

Fig.2 Flow chart of the optimized ABC algorithm.

Initial Food Source: First, it is assumed that the number of initial food sources is SN, the number of employment bee equals $SN/2$, the number of onlooker bee equals $SN/2$. The maximum number of iterations and the maximum number of no-updates are setted. SN initial food sources are generated by Logistic chaos mapping, it is shown in equation (5).

$$x_{k+1}^{j} = 4x_k^j(1-x_k^j) \tag{5}$$

Each food source $x_i\left(i=1,2,...,N\right)$ is a d-imensional vector. The objective function and fitness of the initial population are evaluated according to equations (6) and (7).

$$f(\overset{\vee}{y}_l) = \left|kurt(\overset{\vee}{y}_l)\right| = \left|E\left\{\overset{\vee}{y}_l^{\,4}\right\} - 3\left(E\left\{\overset{\vee}{y}_l^{\,2}\right\}\right)^2\right| \tag{6}$$

$$fit(\overset{\vee}{y}_i) = 1/(1+f(\overset{\vee}{y}_i)) \tag{7}$$

Where $f(\overset{\vee}{y}_i)$ is the objective function of the i-th solution. Then food sources are arranged according to the order of fitness from big to small, the first half is given to the employment bee.

Employment Bee (EB) Phase: New food sources are searched by employment bees in their vicinity. The formula is:

$$v_i^j = x_i^j + \phi_i^j\left(x_i^j - x_k^j\right) \tag{8}$$

Where $k \in \{1,2,...,N\}$, $j \in \{1,2,...,d\}$, and $k \neq i$, k and j are arbitrary numbers in range. ϕ_i^j is a random number between [-1,1]. Fitness of the obtained food source is compared with the original food source. If the fitness is greater than the original food source, it is updated, otherwise it is not updated. Probability of selection of updated food sources is calculated:

$$p_i = fit_i / \sum_{i=1}^{N} fit_i \tag{9}$$

Where p_i is the objective function of the i-th solution.

Onlooker Bee (OB) Phase: The updated food source information is transmitted to onlooker bee by employment bee, then the food source is updated by onlooker bee based on the probability of the food source being selected. If the probability is not less than the average, the new food source will be generated near the optimal solution. If it is less than the average, the new food source will not be generated near the optimal solution. The formula is expressed as follows:

$$v_{ij} = \begin{cases} x_j^{best} + \phi_{ij}\left(x_{ij} - x_{kj}\right), P_i > 1/SN \\ x_{k_1 j} + \phi_{ij}(x_{ij} - x_{k_2 j}), P_i \leq 1/SN \end{cases} \tag{10}$$

Where ϕ_i^j is a random number between [-1, 1]. k is a random number between [1, SN], but does not equal to i. The objective function of the new solution is calculated and compared with the objective function value of the EB phase food source to compose the better solution to the updated food source.

Scout Bee (SB) Phase: No-updated times of food source are determined by Scout bees. If the limit is exceeded, the solution will be regenerated according to equation (9) to replace the original solution.

$$x_{ij} = x_j^{best} + \phi_{ij}\left(x_{ij} - x_{k,j}\right) \tag{11}$$

4 Simulation

In order to verify the separation and optimization effect of the algorithm, the method described above and the traditional ABC algorithm were simulated using MATLAB as a platform. The same source signals for mixing were selected, and two algorithms were chosen to separate them, ten experiments for each algorithm. After simulation, the convergence steps, convergence curves, and the average and variance of similarity coefficients of the two algorithms were compared to verify separation and optimization effect.

Four functions were selected to simulate the source signal in the experiment:

$$S_1 = square(2*\pi*k/16)$$

$$S_2 = \sin\left(1*\pi*k/32\right)$$

$$S_3 = \left(\left(\mathrm{mod}\left(k,23\right)-11\right)/9\right)^5$$

$$S_4 = rand(1,200)$$

The resulting image of source signal is shown in Fig.3.

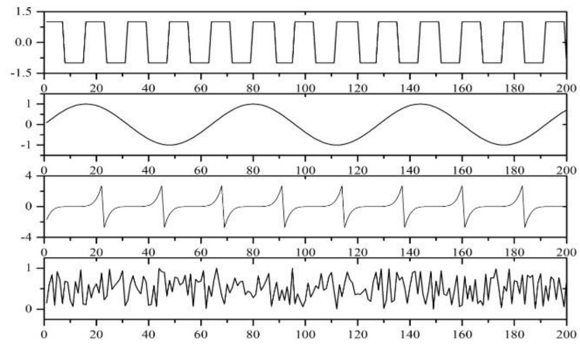

Fig.3 Image of source signal.

Randomly generated matrices were used as mixed matrices:

$$A = \begin{bmatrix} 0.3070 & 0.4083 & 0.9308 & 0.5711 \\ 0.7612 & 0.6223 & 0.6722 & 0.6282 \\ 0.1564 & 0.2918 & 0.1584 & 0.1032 \\ 0.8084 & 0.7772 & 0.4537 & 0.1755 \end{bmatrix}$$

We multiplied the mixing matrix with the source signal matrix to get a mixed signal, as shown in Fig.4.

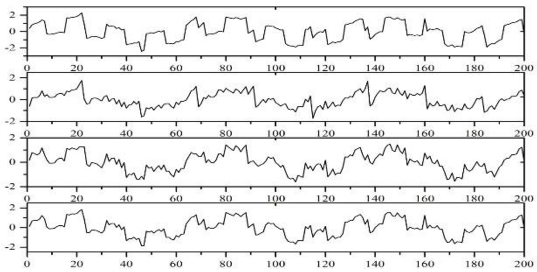

Fig.4 Image of mixed signal.

Four mixed source signals were separated by traditional ABC algorithm and optimized ABC algorithm respectively. The number of initial food sources was set to 20, the number of iterations was set to 500, and the maximum number of no-update times was set to 50.

The images obtained by separating the two algorithms to obtain the unmixed signals are shown in Fig.5 and Fig.6 respectively.

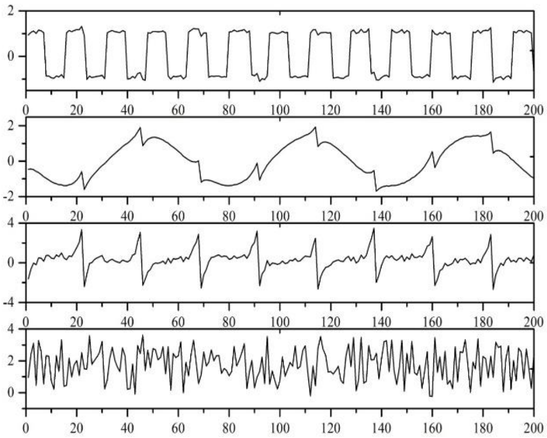

Fig.5 Separative signal of traditional ABC algorithm.

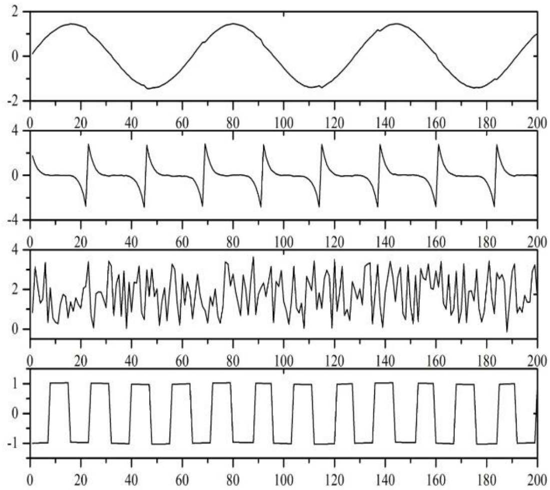

Fig.6 Separative signal of optimized ABC algorithm.

It can be seen from the separative signal images of the two algorithms that both algorithms can restore the source signal effectively. However, compared with the separative image of square wave signal, sine signal and super-Gaussian signal, it can be found that the optimized ABC algorithm has better reduction than the traditional ABC algorithm.

The convergence curves of the fitness function and the objective function of the two algorithms are shown in Fig.7 and Fig.8, respectively.

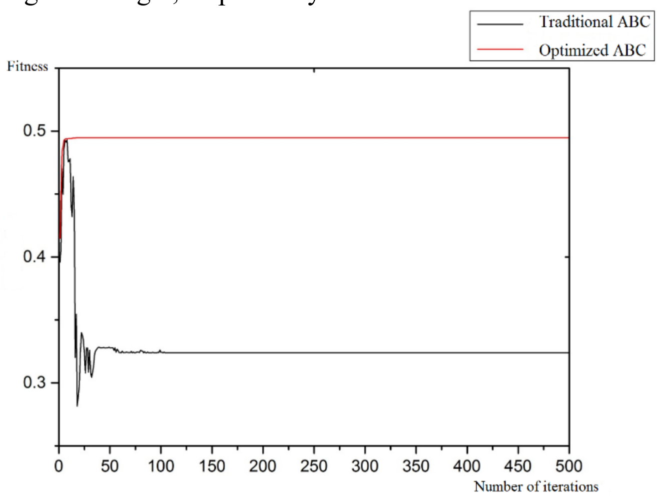

Fig.7 Convergence curves of fitness function.

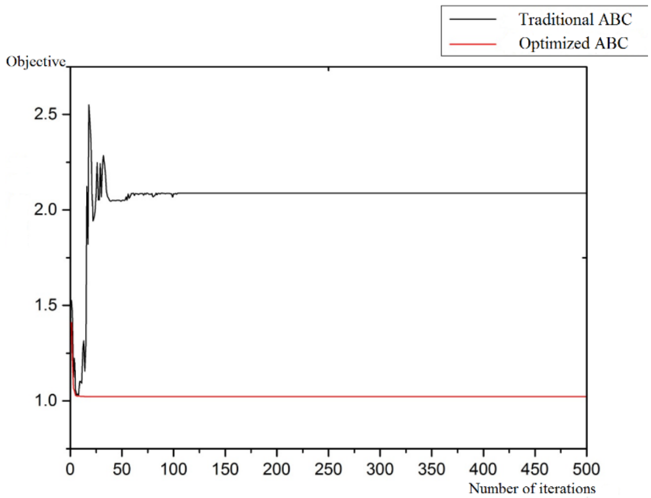

Fig.8 Convergence curves of objective function.

The red curve represents the optimized ABC algorithm, the black represents the traditional ABC algorithm. The average convergence step of the traditional artificial bee colony algorithm was 102, and the average convergence step of the optimized artificial bee colony algorithm was 54. Therefore, the convergence speed has been optimized.

After the separative signal is obtained, the separation effect of the algorithm is determined by the correlation coefficient with the source signal, and the calculation formula of the correlation coefficient is:

$$\xi_{ij} = \xi\left(y_i, s_j\right) = \frac{\left|\sum_{i=1}^{N} y_i\left(t\right) s_j\left(t\right)\right|}{\sqrt{\sum_{i=1}^{N} y_i^2\left(t\right) \sum_{j=1}^{M} s_j^2\left(t\right)}} \qquad (12)$$

where, y_i is the i-th separative signal obtained after blind source separation, s_j is original signal, ξ_{ij} is correlation coefficient between the i-th and j-th source signal. If ξ_{ij} equals to 1, it shows that the i-th separative signal is exactly the same as the j-th source signal. Since there is an estimation or the like in the separation process, similarity coefficient cannot be equal to 1 and only needs to be close to 1. If the similarity coefficient is close to 0, the separation effect of the algorithm is poor. The average similarity coefficient separated by the traditional algorithm is shown in Table 1. The average similarity coefficient separated by the optimization algorithm is shown in Table 2. Only from the correlation coefficient matrix of the separative signal and the source signal obtained by the two blind source separation algorithms, the artificial bee colony optimization algorithm is slightly better than the classical artificial bee colony optimization algorithm.

Table 1 Similarity coefficient of traditional ABC algorithm

	Similarity coefficient			
1	0.9998	0.8992	0.9711	0.9807
2	1.0000	0.8276	0.9309	0.9137
3	0.9841	0.9690	0.9586	0.8872
4	0.9999	0.9807	0.9851	0.8486
5	1.0000	0.8681	0.9894	0.9675
6	0.9999	0.9994	0.8777	0.9877
7	0.9902	0.8984	0.9505	0.9555
8	1.0000	0.9228	0.8984	0.8972
9	0.9997	0.9327	0.9469	0.8377
10	0.9999	0.8974	0.8955	0.9437

Table 2 Similarity coefficient of optimized ABC algorithm

	Similarity coefficient			
1	0.9870	0.9933	0.9224	0.9860
2	1.0000	0.9430	0.9503	0.9842
3	0.9999	0.9700	0.9082	0.9272
4	0.9999	0.9532	0.9883	0.9930
5	1.0000	0.9351	0.9232	0.9130
6	1.0000	0.9936	0.9675	0.9325
7	0.9993	0.9875	0.9583	0.9085
8	1.0000	0.9771	0.9335	0.9031
9	0.9788	0.9309	0.9967	0.9440
10	1.0000	0.9195	0.9275	0.9619

Calculate the variance of the similarity coefficient of the ten groups of data. The variance of the similarity coefficient of the traditional algorithm is 0.0026, and the variance of the similarity coefficient of the optimization algorithm is 0.0011. Therefore, the stability of the optimization algorithm is better than the traditional algorithm. In summary, it is proved that the optimization of this paper is effective.

The main reasons for the above optimization effect are as following:

(1) Logistic Chaos Mapping is introduced into food source initialization stage. Because the chaotic sequences generated by Logic maps have better ergodicity, randomness, and regularity than randomly generated food sources in traditional bee colony algorithms. The mapping calculation is simple and easy to use, and it improves the global optimizing ability.

(2) Update strategy in OB phase is improved. Different update strategies are selected based on the probability of selection of specific food source in the OB phase. If the probability of being selected for a certain food source is greater than the average probability, the

search is updated near the current optimal food source, otherwise the search is updated near the original food source. The purpose of this approach is to speed up optimization while ensuring the overall optimization of the food source. Food source with a low probability of selection was searched within the neighborhood ensures of the global nature of the food source and avoids falling into a local optimum. The food source with a high probability of being selected was searched in the neighborhood of the current optimal solution, speeding up the speed of optimization.

(3) Adjustment strategy optimization. In the traditional ABC algorithm, if the number of non-renewal times of the food source reaches a limited number of times, a new food source is randomly generated and replaced. This practice has blindness and affects the efficiency of the algorithm, and it is performed in this algorithm improvements. New food source was generated based on the current optimization results. This makes the adjustment strategy directional, avoids the blindness of random initialization, and improves the optimization efficiency of the algorithm.

5 Summary

The initialization phase, update strategy and adjustment strategy of the traditional artificial bee colony algorithm are optimized in this paper. It is verified by MATLAB simulation that the optimization algorithm has better stability, convergence speed, and globality than the traditional algorithm. The algorithm was applied to the fault diagnosis process to make a preliminary verification.

Artificial bee colony algorithm has the characteristics of few parameters and strong robustness. It has good separation ability for the linear mixed signal, but the separation ability of the nonlinear mixed signal is weak, so it should be solved in the future research. Artificial bee colony algorithm can be combined with other intelligent algorithms to develop more advanced and powerful intelligent algorithms.

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