ROTOR VIBRATION FEATURE RECOGNITION BASED ON PARTICLE SWARM OPTIMIZATION (PSO)

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ABSTRACT: To solve the problem of large computation and poor convergence of rotor fault diagnosis and recognition signal processing methods, this paper proposes a particle swarm optimization algorithm based on fourth-order cumulant. The algorithm takes the fourth-order cumulant of the separated signals as the fitness function to simulate the impact signal of the rotor. The frequency characteristics of the second separation signal are 0.32hz, 0.64hz of the double frequency and 1.27hz of the quadruple frequency, which conform to the frequency domain characteristics of the simulated rotor misalignment fault signal. The frequency of the third separated signal has no obvious characteristic and is judged as noise signal. The fourth independent component represents a frequency signal with a fixed frequency of 0.16hz, which is judged to be a signal simulating the periodic vibration of the rotor. The results show that the standard particle swarm optimization (pso) algorithm can accurately extract the vibration signals of the rotor and identify and extract the fault types.

KEYWORDS: Rotor system; Feature recognition; Particle swarm optimization

1.INTRODUCTION

With the modern development of industry, the structure of mechanical production equipment is increasingly complex, generally operating in the production environment of high temperature, high pressure, high load and high speed (Lin, Hwang, 2016). There are various types of machinery and equipment in the manufacturing industry. Due to the limitation of driving mode, many key equipment are large rotating machines, and the trouble-free operation of the rotor largely determines the safe operation of the equipment (Wen et al., 2017).

According to statistics, more than 60% of mechanical equipment faults are caused by vibration. For the equipment fault diagnosis method, the method with the best effect and the most commonly used method is vibration analysis method, which obtains the data containing information through the sensor and obtains the rotor vibration characteristics in the signal through a series of processing (Wang et al., 2018). However, the actual industrial production environment where the rotor is located is often complex and there are many interference signals. Therefore, after the sensor collects the signals, the filtering of interference signals, the extraction of fault signals and the identification of fault categories are the prerequisites for rotor operation state monitoring and fault diagnosis (Lei et al., 2018).

Rotor fault diagnosis and recognition signal processing method of large amount of calculation and convergence of poor problem, this paper will be based on particle swarm optimization (pso) algorithm, is put forward based on fourth-order cumulants fitness function, using the particle swarm algorithm for complex signal simulation separation matrix, and combined with fault simulation experiment system, verify the algorithm validity and the reliability of
convergence.

2. LITERATURE REVIEW

Aiming at the small vibration of the rotor system of centrifugal compressor, and the characteristics of vibration signal being non-stationary, non-linear and accompanied noise interference, Couceiro proposed a fault identification method of overall average empirical mode decomposition (Couceiro, Ghamisi, 2016). Wang G.G. studied a matrix joint approximate diagonalization independent element analysis (JADE-ICA) method based on high order statistical information of source signals, and applied it to blind source separation of rolling bearing fault acoustic emission (AE) signals (Wang et al., 2017). Yao B. proposed a rolling bearing fault feature extraction method based on variational mode decomposition and energy operator to solve the problems of low SNR of early fault vibration signals and difficulty in fault feature extraction of rolling bearings (Yao et al., 2017). Singh R. P. proposed a method for extracting bearing fault features of wind turbine based on blind source separation and manifold learning algorithm (Singh et al., 2017).

3. RESEARCH METHODS

3.1 Description of Particle Swarm Optimization

Of solving problems, through the movement of the particles and the fitness function iterative particle velocity and position updating continuously, regardless of the particle's mass and volume, the speed of flight determine the particle flying distance and the direction of flight, according to the particle swarm algorithm has the characteristics of global optimization and not rely on the gradient information, through fitness function value to measure whether the location to achieve the optimal global optimization can be realized, finally find the optimal location, is the optimal solution (Chatterjee et al., 2017).

The mathematical description of the optimization iterative process of the above algorithm is as follows: defined in the n-dimensional target solution space, the particle group $X = (X_1, X_2, X_3,...X_n)$, randomly set an initial value in the space for repeated iteration, and each particle in the population is a possible solution of the algorithm, using the vector $D_i=(D_{i1}, D_{i2},...,D_{in})$ and $V_i=(V_{i1}, V_{i2},...,V_{in})$ respectively represent the position vector and flight velocity vector of the ith particle. The optimization in each iteration of the particle is realized by tracking the extreme values of the two vectors. The updated optimal value is called the individual extreme value $P_i=(P_{i1}, P_{i2},...,P_{in})$ can also be viewed as each particle's flight experience. The optimal value of all individual extremum in each iteration is called the current global extremum. In the iteration process, the vector $P_e=(P_{e1}, P_{e2},...,P_{en})$, also known as group experience (Peng et al., 2017). The update mode of the speed and position of each iteration in the algorithm is based on formula (1) and formula (2):

$$V_{i}^{t+1}=V_{i}^{t}+c_1r_1 \times (P_{i}^{t}-D_{i})+c_2r_2 \times (P_{e}^{t}-D_{i}) \tag{1}$$

$$D_{i}^{t+1}=D_{i}^{t}+V_{i}^{t+1} \tag{2}$$

Among them: $I = 1, 2, ..., n$. $T$ is the number of current iterations, that is, the number of steps of particle flight; $C_1$ and $C_2$ are learning factors, also known as acceleration factors, which are non-negative; $r_1$ and $r_2$ for between [0, 1) interval random number; for after the first t iteration for the ith particle $P_{best}$ search to individual optimal position, said the group after optimization iteration t time of the current global optimal location $G_{best}$. Update the rate at which the type (1) formula can be analyzed separately, the first part shows the velocity influence on the current speed, the previous iteration particle is considered a particle "inertia" or "momentum"; the second part is called the particle's "self cognition", is the location of particles on their own past memories and experience; that the third part is the "social cognition" part of the particle, It reflects the information sharing and cooperation among
particles, as well as the ability of particles to approach the optimal position, so that particles can search in a wider space. The termination condition of iteration is generally set as the maximum number of iterations or the fitness of the global optimal value searched by the algorithm to meet the predetermined threshold according to the specific problem to be solved.

3.2 Particle Swarm Optimization Process

According to the description of the algorithm, the steps to summarize the basic particle swarm optimization algorithm are as follows:

Step 1: determine the particle dimension according to the problem dimension, set the initial position and initial velocity of the particle, and ensure that it is in the solution space;

Step 2: set the initial position of each particle as Pbest, and calculate its fitness; Set the particle with the best fitness as the global optimal position Gbest;

Step 3: update the particles according to formula (1) and (2), and calculate the fitness of each particle;

Step 4: take the maximum of the particle’s current fitness and the individual extreme value Pbest fitness, assign the fitness value to Pbest, and record the current coordinate as the position of Pbest;

Step 5: compare the fitness of the individual extreme value Pbest and the global optimal position Gbest. If the fitness of Pbest is better, assign the value of Pbest position to Gbest and record the current coordinate position; otherwise, Gbest remains unchanged.

Step 6: judge whether the iteration results meet the set termination conditions. When the iteration termination conditions are met, stop the iteration and output the optimal solution at the same time. If the termination conditions are not met, the algorithm returns to step 3 for further calculation.

The algorithm flow is shown in figure 1.

3.3 Standard Particle Swarm Optimization

Basic particle swarm optimization algorithm still shows some shortcomings in practical application, such as easy to be trapped in local optimal, slow speed in the late convergence, etc. However, due to the simple principle of the algorithm, easy to understand and use, experts at home and abroad put forward many improvements to the algorithm parameters, so as to improve its performance. Shi first proposed to apply inertia weight to PSO algorithm in the paper published at the international conference on evolutionary computing in 1998 to ensure the inheritance of the previous generation’s velocity by particles, as shown in equation (3):

\[ V_{it}^{new} = \omega V_{it}^{old} + c_1 r_1 \times (P_{it} - D_{it}) + c_2 r_2 \times (P_{g} - D_{i}) \]  

(3)

Inertia weight \( \omega \) is a different parameter compared with the basic particle swarm optimization algorithm. When \( \omega \) is large, the current flying speed of particles is modified here, which makes the velocity of particle swarm...
optimization more effective for the search of solution space. When omega is large, the algorithm endows the particle with a larger flight speed and obtains a stronger global search ability. When the value is small, the local search ability of particles is strengthened. In the process of iteration, the dynamic adjustment of the algorithm can control the influence of the empirical velocity on the current level, so that the search ability and convergence speed of particles in the iterative process can reach a balance. According to the linear decreasing weight strategy proposed by Shi, a larger value of $\omega$ is obtained in the early stage, which is beneficial to global search and makes the algorithm jump out of local optimization. In the later stage, a smaller value of $\omega$ with a good local search ability was obtained, which accelerated the convergence. According to formula (4), the weight was decreased linearly within the interval $[0.9,0.4]$:

$$\omega(t) = \omega_{\text{max}} - (\omega_{\text{max}} - \omega_{\text{min}}) \times \frac{t}{T}$$  

(4)

In this equation, $\omega_i(t)$ represents the inertia weight of the $i$th particle in the TTH iteration, $T$ is the maximum number of iterations, and the variation range of the inertia weight is limited by $\omega_{\text{min}}$ and $\omega_{\text{max}}$.

### 3.4 Fitness Function

The standard particle swarm optimization (PSO) algorithm is introduced into blind source separation to separate the simulated signal from the experimental signal. For linear instantaneous mixed signal blind source separation, the selection of fitness function, there are many here to collected according to the composite signal is gaussian separation criterion, determine the signal of the fourth-order cumulant as fitness function, according to the signal independence requirements, compared with the source signals, separation of non gaussian signal is stronger, in the blind source separation, the separation of the signal of fourth-order cumulants as fitness function:

$$f(y) = \sum_{\gamma=1}^{4} k_i^{(y)} = \sum_{\gamma=1}^{4} \left[ E[y_i^\gamma] - E[y_i^\gamma] E[y_i^\gamma] \right]$$  

(5)

Using the standard particle swarm algorithm for the optimization of the separation of the signal of the fourth-order cumulant to maximize, when the type of fitness function $f(y)$ that the greater the signal of the fourth-order cumulant, the greater the separation, the stronger the non gaussian signal, fitness function to obtain the maximum, can maintain to achieve the effect of blind source separation, separation matrix $W$. In order to make the solution vectors orthogonal to each other, the vectors were normalized after each iteration. According to the Gram-schmidt orthogonalization method, the orthogonal formula was obtained as follows:

$$W_p = W_p - \sum_{k=1}^{p-1} (W_p^T W_k) W_k$$  

(6)

Where, $p_w$ is the p(p=1,2...,m) column element array, set the number of source signals equal to the number of collected signals, set as m.

The normalized separation matrix can be obtained as follows:

$$W_p = W_p / \|W_p\|$$  

(7)

### 3.5 Flow of Algorithm

The first step of particle swarm optimization is to initialize the population in the solution space of a specific problem, and then determine a fitness value for it according to the fitness function. According to the iterative formula of the algorithm, the particle searches for the optimal solution in the solution space. The particle swarm optimization algorithm with fourth-order cumulant as the objective function searches in the solution space, and the calculation steps are as follows:

Step 1: centralize and whiten the signal;

Step 2: set the initial random mixing matrix $W$ to ensure that it is in the solution space;

Step 3: initialize the particle population size and select n particles. As the initial position vector
Di of the particle, gong set the initial velocity of the particle to 0.1Di.

Step 4: set the initial position of each particle as Pbest, and calculate its fitness; Set the particle with the best fitness as the global optimal position Gbest;

Step 5: update the particles according to formulas (2) and (3), and calculate the fitness of each particle;

Step 6: normalize each column of W to avoid repeatedly separating the same signal, and normalize W to ensure the stability of separation;

Step 7: take the maximum of the particle's current fitness and the individual extreme value Pbest fitness, assign the fitness value to Pbest, and record the current coordinate as the position of Pbest;

Step 8: compare the fitness of the individual extreme value Pbest and the global optimal position Gbest. If the fitness of Pbest is better, assign the value of Pbest position to Gbest and record the current coordinate position; otherwise, Gbest remains unchanged.

Step 9: judge whether the iteration results meet the set termination conditions. If not, the algorithm returns to step 5 for further calculation. When the iteration terminates, the iteration is stopped and the separation matrix W is output.

Step 10: output the separation signal.

4. RESULTS AND ANALYSIS

4.1 Simulation Experiment Results

In order to verify the effectiveness of the proposed algorithm, four typical signals are simulated with a sampling point of 1000. The function formula of the source signal is as follows:

$$s(t) = \begin{pmatrix} s_1(t) \\ s_2(t) \\ s_3(t) \\ s_4(t) \end{pmatrix} = \begin{pmatrix} \sin t \\ \sin 2t + \sin 4t + \sin 8t \\ \text{sawtooth}(2\pi 0.08t) \\ 1/n(t) \end{pmatrix}$$

(8)

Where, the source signal s1(t) simulates the periodic vibration signal, s2(t) simulates the rotor misaligned signal, s3(t) simulates the shock signal, and s4(t) simulates the noise signal. The above four-channel signals are linearly mixed into a composite observation signal through the normal distribution matrix randomly generated by the computer. The random matrix A is shown as follows:

$$A = \begin{pmatrix} 0.0649 & 0.2329 & -0.5278 & 0.6850 \\ -0.3590 & -0.7902 & -0.1649 & 0.9319 \\ -1.2751 & 1.0946 & 0.7187 & 1.2944 \\ 0.7901 & -0.1056 & -0.5619 & 1.1511 \end{pmatrix}$$

Get the compound signal, and whiten it, remove the coupling between each component of the compound signal, and get the whitening signal as shown in figure 2.
The algorithm proposed in this chapter is used to separate the whitening signal. In order to demonstrate the convergence of the algorithm, the maximum iteration number \( T \) of the algorithm is set as 100, the initial particle search range and speed are respectively \([-10,10]\), \([-1,1]\), and the acceleration factors \( c_1 \) and \( c_2 \) are respectively set as 1.5. The four independent components obtained by the algorithm are \( y_1(T), y_2(T), y_3(T), \) and \( y_4(T) \). Therefore, it is judged as the impact signal of the simulated rotor. The frequency characteristics of the second separation signal are 0.32Hz, 0.64Hz of the double frequency and 1.27Hz of the quadruple frequency, which conform to the frequency domain characteristics of the simulated rotor misalignment fault signal. The frequency of the third separated signal has no obvious characteristic and is judged as noise signal. The fourth independent component represents a frequency signal with a fixed frequency of 0.16Hz, which is judged to be a signal simulating the periodic vibration of the rotor. The fitness value convergence curve of the algorithm is shown in figure 3.

![Algorithm convergence curve](image)

As can be seen from figure 3, when the number of iterations reaches 17, the algorithm has basically converged, and its fitness function value remains basically unchanged, indicating that the convergence speed is fast. The similitude coefficient matrix between the separated independent components and the source signals was constructed to quantitatively evaluate the accuracy of the signal separation, and the similitude coefficient matrix was calculated as follows:

\[
\mathbf{S}_y = \begin{bmatrix}
-0.0333 & -0.0003 & 0.0094 & 0.9841 \\
0.0061 & 0.9750 & 0.0228 & 0.0002 \\
-0.9123 & -0.0809 & -0.0112 & -0.2431 \\
0.0012 & -0.0019 & 0.9826 & -0.0236
\end{bmatrix}
\]

Among them: you can see in each row and each column of the matrix is the absolute value of coefficient of only one close to 1, to annotate the coefficient, said that the separate signal component and the correlation of source signal component, the algorithm for extracting the characteristics of the signal recognition and has higher accuracy, and successfully realized the effective separation of multiple signals.
4.2 Rotor Vibration Characteristic Separation Experiment

For validation of the particle swarm algorithm based on fourth-order cumulant is actual separation effect, the algorithm is applied to the experiment system of rotor dynamics experiment, an analysis of the measured vibration signal of rotor, the rotor dynamics experiment system USES two IEPE sensors were installed on both sides of the base, and close to the side of the bearing seat, to be able to collect to two difference is bigger, facilitate subsequent processing of vibration signals, the specific installation position as shown in figure 4.

![Schematic diagram of sensor installation in rotor dynamics experiment system](image)

Under the actual operating conditions of the rotor, the signals collected by each sensor are not idealized signals with a single component, but often contain signals with complex multi-channel frequencies. In order to meet the assumption of the algorithm on the number of acquisition channels, two sensors were used to collect signals during the experiment. The sampling frequency was 1000Hz, the sampling time was 17s, and the motor speed was 3200r/min. In order to effectively identify the waveform, 2000 points were intercepted for calculation. The mixed signals collected by channel 1 and channel 2 have many frequency features with large energy in the frequency domain. The rotor's rotation frequency and its frequency doubling are both present in the two collected signals. It can be seen that the rotor fault signals of different types are overlapped together, and the fault types cannot be distinguished. First, the mixed signal is preprocessed.

The application of the particle swarm optimization (pso) based on the fourth-order cumulant to separate the pre-processed signals verifies the feasibility of identifying and extracting rotor vibration features of the PSO.

5. CONCLUSION

Based on particle swarm algorithm is summarized on the basis of mathematical description and the relevant parameters, the construction of a signal as the fitness function of fourth-order cumulant, through the establishment of four sets of simulated rotor fault signal simulation, verify the effectiveness of proposed algorithm in signal separation, and combined with correlation coefficient analysis, further proves that the accuracy of the algorithm separation results. The rotor fault signal was analyzed experimentally in combination with the rotor dynamics experimental system. As can be seen from the separated waveforms, the characteristic frequencies of different fault types were accurately recovered with faster convergence speed and higher accuracy, which has certain practical significance.
6. REFERENCES

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