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The Study of Rotor Fault Feature Recognition Based on EEMD-ICA Denoising Method

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Abstract. Aiming at the problem of large noise interference and difficulty in extracting faults during rotor fault diagnosis, a signal de-noising method based on EEMD-ICA was proposed. This method can effectively suppress the modal aliasing phenomenon and accurately separate the noise components contained in signals. Experimental results show that the denoising effect of proposed method was obvious and the rotor fault features can be effectively identified.

1. Introduction

As the core component of the motor, the rotor performance directly affects the overall operating state of the rotating machine. The reliability and accuracy of fault diagnosis can be directly affected by feature extraction and pattern recognition [1-3]. During the operation of the rotor, noise components are unavoidably introduced in the signal acquisition process due to the complexity of the working environment, the acquisition device, and the vibration. The accuracy of rotor fault diagnosis will be seriously affected.

In recent years, although the mechanical equipment condition monitoring and fault signal diagnosis techniques have achieved certain results [2, 3], there are still deficiencies in fault signal feature extraction. For example, due to the complex working conditions of mechanical equipment, the collection of fault feature signals contains relatively complex signals. The noise, the signal channels affect with each other in the acquisition process, the fault feature signal and the interference signal are superimposed, so that subsequent fault extraction and signal analysis are seriously affected, so extracting effective signals and removing the interference signal components are the key to fault diagnosis.

The BSS method has been gradually matured at the theoretical level. In the application of rotor fault diagnosis [2]. The BSS method provides an effective way for the extraction and determination of fault features and has guiding significance for the detection of rotor faults in the early and late stages. The Independent Component Analysis (ICA) method is a powerful signal processing method, which belongs to the BSS method [5, 6]. It has been more and more concerned by the academic community. Many domestic relevant experts and scholars have also payed more and more attention to the development of this technology. However, the requirements for source signals in the ICA model are too ideal. In the face of complex signal channels, independent component analysis cannot effectively achieve accurate separation of source signals. Therefore, a signal de-noising method based on EEMD-ICA is proposed and applied to rotor failures. Signal feature extraction decomposes the source signal into several eigenmode functions through the set of Empirical Mode Decomposition (EEMD). As the

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signal path of ICA, it enhances the independence of the source signals and thus successfully separates the noise signal. The hidden fault features are identified in the mixed signal.

2. EEMD

In this paper, the EEMD method is used to improve the accuracy of the previous EMD method in the process of rotor fault diagnosis [4-8]. The more accurate fault feature status is obtained. The specific steps are as follows:

(1) A certain intensity white noise signal is added to the acquisition signal *s(t)*. The overall average number of times M is initialized and the noise amplitude is added, m=1.

$$s(t) = s_m(t) + n_m(t) \quad (1)$$

Among them, the noise signal is joined into $s_m(t)$ after m times, $n_m(t)$ is the noise after m times.

(2) EMD decomposes the added white noise signal.

(3) Repeat steps (1) and (2) to add different white noise sequences until the number of decompositions is m=M.

(4) The average IMF of each decomposition $y_n(t)$ is solved.

$$y_n(t) = \frac{1}{M}\sum_{m=1}^{M} C_{mn} \quad n=1,2\ldots\ldots, M \quad (2)$$

Since the added white noise is uniformly distributed in the entire time-frequency space, the added noises are independent of each other after each time of EMD decomposition, so the added noise cancel each other out. Thereby the modal aliasing phenomenon is canceled.

3. ICA

Based on rotor fault diagnosis, N sensors are used to acquire signals. Each of the collected observation units contains independent source signals. The formula for mixed signals is as follows:

$$x = As \quad (3)$$

Among them, S is the source signal vector, A is a mixing matrix, and both the mixed signal and the source signal are zero-mean. The source signals are mutually independent. From the model, we can see that only the relevant information of the propagation path can be obtained to separate the independent source signals. The separation process is expressed as:

$$y(t) = Wx(t) = WAs(t) = \hat{s} \quad (4)$$

Independent source signals cannot be obtained directly. If there are no other constraints, the solution of the formula must be multi-solution. Under some limited conditions, the unique solution of the equation can be obtained based on the prior knowledge and statistical characteristics. ICA flow chart is as follows:

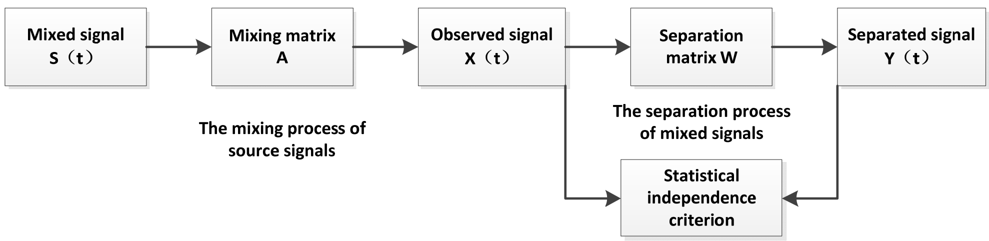

Figure 1 ICA flow chart

From Fig. 1, it can be seen that the extraction of independent components is simplified as seeking the separation matrix. Here, the criterion of maximum negative entropy and the improved fixed point fast iterative algorithm are used to seek the separation matrix. In response to the fact that the relevant source signals do not fully satisfy the independent assumptions, the EEMD-ICA method is proposed, and the process based on the EEMD-ICA method is shown in Fig. 2:

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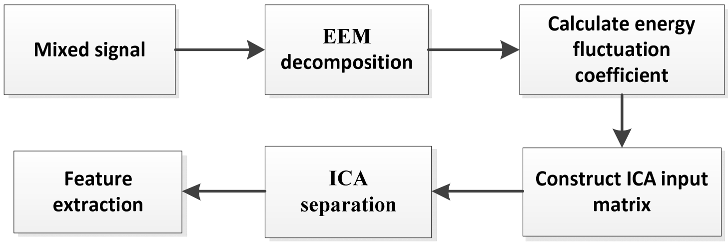
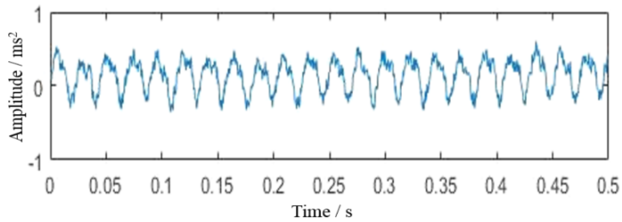


Figure 2 EEMD-ICA signal processing flow chart

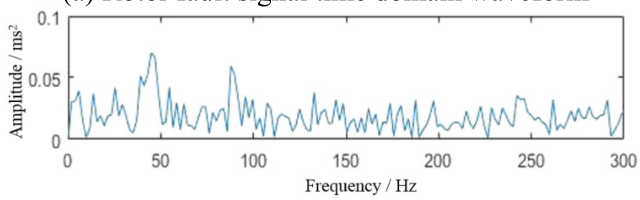
4. Test Analysis

The EEMD-ICA method is used for fault identification of rotor fault signals, in which the test bench model is ZT-3. This test bench is driven by a DC-excited parallel-excited motor. The rated current of the motor is 2.5A and the output power is 250W. The signal acquisition and analysis system mainly includes: AI005 accelerometer, charge amplifier, KM3840 data collector and computer. During the test, the signal sampling frequency is 2000 Hz and the motor speed is 2694 r/min. Therefore, the rotor rotation frequency is about 44.9 Hz.

As Fig. 3 shows, the time domain and corresponding frequency domain plots of the rotor imbalance fault signal. From Fig. 3(a), the background noise reduces the signal to noise ratio of the signal and weakens the impact component of the signal. Figure 3(b) Spectrum analysis shows that there are multiple frequency bands in the frequency domain and it is impossible to observe the fault feature frequency clearly.



(a) Rotor fault signal time domain waveform



(b) Rotor fault signal spectrum

Figure 3 The time domain and corresponding frequency domain of the rotor imbalance fault signal

This method is used to decompose the signal by EEMD. In the decomposition process, the overall average number of times is I = 100. The standard deviation of adding white noise is 0.2. A total of 9 IMF components are obtained. The first 6 IMF components are shown in Fig. 4. The energy fluctuation coefficients of the IMF components are shown in Fig. 5.

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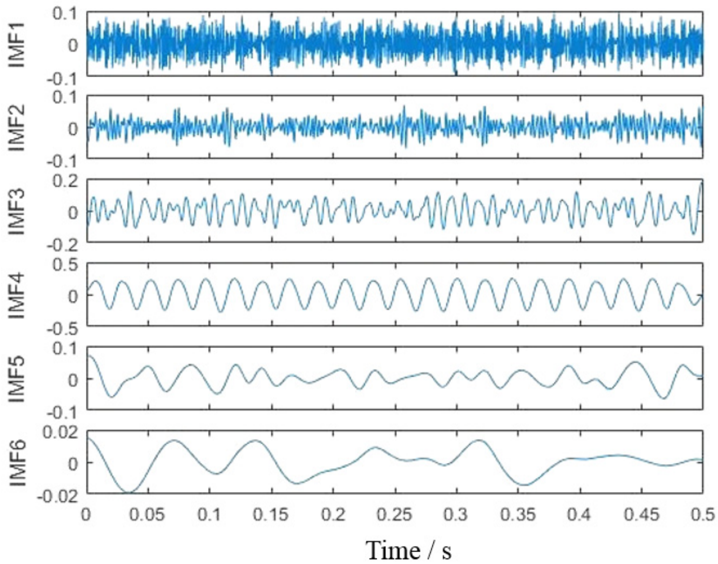


Figure 4 Rotor fault signal EEMD decomposition results

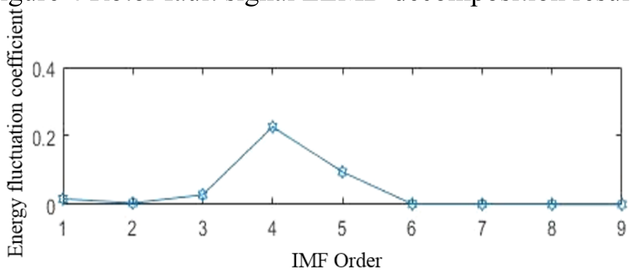
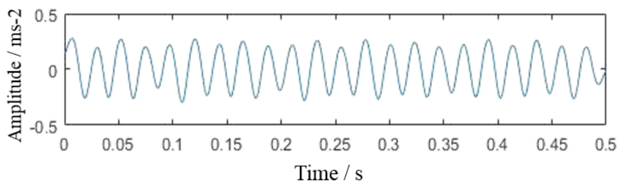
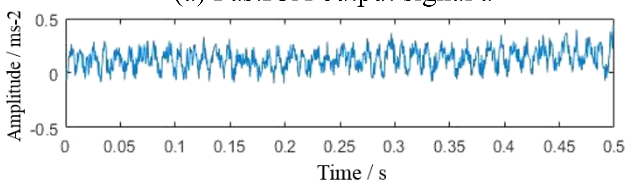


Fig. 5 Energy Fluctuation Factor of Each IMF Component

From Fig. 5, it can be seen that the energy fluctuation coefficients of the IMF4 and IMF5 components are large, indicating that they contain more original signal feature information. For this purpose, the remaining IMF components are summed to construct a virtual noise channel, and an ICA input matrix is formed with the original signal, which is separated using a FastICA algorithm. The result is shown in Fig. 6.



(a) FastICA output signal a



(b) FastICA output signal b

Figure 6 FastICA algorithm output signal

It can be seen from Fig. 6 that the output signal a is a fault source signal containing rotor fault characteristic information, and most of the high frequency noise interference components are filtered out effectively. The signal waveform highlights the original signal information. A spectrum analysis was performed on this signal and the resulting spectrum is shown in Figure 7.

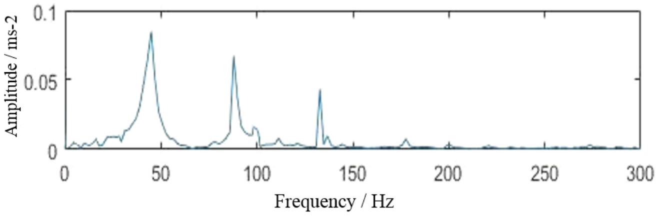


Figure 7 Spectrum of FastICA output signal 1

It can be seen from Fig. 7 the proposed method purifies the rotor fault signal and extracts its fault characteristic frequency effectively. From the frequency spectrum, it can be clearly seen that there are three dominant frequencies f1 = 44.9 Hz, f2 = 87.9 Hz, and f3 = 133.9 Hz, which are about 1 times frequency shift, 2 times frequency shift, and 3 times frequency shift of the rotor.

When there is an unbalanced fault in the rotor, it will cause radial vibration of the rotor. In the vibration frequency of the rotor, it will have a frequency component which is consistent with the frequency of the rotor. Due to nonlinear reasons, it is often accompanied by high frequency ingredient. The frequency spectrum of the rotor fault signal is completely consistent with the above fault characteristics. It can be inferred that a rotor imbalance fault has occurred in the rotor system and the effectiveness of the proposed method is proved.

5. Conclusion

This paper discusses the application of EEMD-ICA denoising method in rotor fault signal feature recognition. EEMD method is used to decompose the rotor fault signal. The IMF components sensitive to fault information are selected through the principle of energy fluctuation coefficient to construct virtual noise. The channel obtains the input signal of ICA. The signal is reconstructed by ICA and detailed information of the fault feature signal is extracted. Through the analysis of the rotor fault signals, the effectiveness of the proposed method is verified.

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