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Research on Rolling Bearing Fault Feature Extraction Based on Kurtosis Optimized Singular Spectrum Decomposition

Hongyu Zhou*

College of International Education, Changchun University of Technology, Changchun, China, 130000
**Corresponding author: 3039047235@qq.com*

Abstract: *Aiming at the challenges of extracting weak bearing faults under strong background noise and determining the optimal component in singular spectrum decomposition (SSD) for rolling bearings, this study proposes a singular spectrum decomposition method based on kurtosis optimization. Firstly, the bearing vibration signal is decomposed using SSD to obtain multiple singular spectral components (SSC). Then, based on the sensitivity of bearing faults to kurtosis, the kurtosis value of each component is calculated, and the optimal component is selected at the point of maximum kurtosis. Finally, the selected component undergoes envelope demodulation to obtain the characteristic frequency and complete fault diagnosis. Experimental results demonstrate that the proposed method effectively extracts bearing faults under strong background noise. It also provides a reliable tool for early fault diagnosis of rolling bearings in industrial equipment, offering significant practical engineering value in reducing enterprise operational costs and ensuring the safe and stable operation of critical equipment.*

Keywords: *Vibration Signal; Singular Spectrum Decomposition (SSD); Kurtosis; Fault Diagnosis; Rolling Bearings*

1. Introduction

With the advancement of technology and the widespread adoption of industrial Internet of Things, modern mechanical equipment is evolving rapidly towards larger size, centralized operation, high precision, and intelligence. Its operating environment is more demanding and usage frequency is higher. Some equipment needs to operate continuously, which puts higher requirements on equipment performance, efficiency, and reliability. The health status of core components becomes crucial - once they fail, it not only may cause equipment to stop or malfunction, but also may lead to huge economic losses and even safety accidents [1].

Bearings, as the core components of mechanical systems, their working conditions directly determine the efficiency and safety of equipment operation. Affected by the complex and variable industrial environment, bearings are prone to various failures, which not only increase maintenance costs but also may interfere with the normal operation of equipment and threaten the safety of operators. Therefore, bearing condition monitoring and data analysis have become the core issues in the field of preventive maintenance and fault diagnosis. During the operation of mechanical equipment, the vibration signals of bearings contain a large amount of health information: when a bearing fails, the vibration signal will present periodic pulse characteristics, and different fault types correspond to different characteristic frequencies. However, the actually collected vibration signals often have nonlinearity, non-stationarity, and are severely disturbed by noise, making it difficult to extract fault characteristics [2].

In conclusion, bearing condition monitoring and fault feature extraction are important means to ensure the efficient and safe operation of mechanical equipment, and how to accurately and efficiently identify and analyze fault features in the complex and variable vibration signals remains the core issue in current research and practice.

For the problem of fault feature extraction of bearing vibration signals, researchers at home and abroad have carried out extensive and in-depth discussions. They have adopted a variety of signal processing techniques. Konstantin Dragomiretskiy et al. [1] first introduced the concept of variational modal decomposition, extending the classical Wiener filter to multiple adaptive frequency bands, and demonstrated outstanding performance across a range of synthetic and real-world data. Yang et al. [3] summarizes the characteristics of variational mode decomposition and empirical mode decomposition

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methods. Through multiple experiments, it shows that VMD is superior to EMD and other methods, especially in real-time frequency feature extraction. Zhao et al. [4] proposed a combined approach using least squares fitting (LSF) and empirical mode decomposition (EMD) to filter out interference signals from the raw signal. This method compensates for the shortcomings of either technique alone in handling low-frequency trend components, thereby enhancing the reliability of vibration signal analysis. Wang et al. [5] proposed a method for extracting spindle failure features using SSD joint mutual information, which effectively solved the problems of poor noise reduction capability of the singular spectrum algorithm in signal-to-noise ratio and the difficulty of determining the number of sensitive components. However, the above methods have some issues, such as poor performance in environments with strong background noise and difficulty in parameter selection.

In this paper, for the problem that it is more difficult to extract bearing faults under strong noise and it is difficult to determine the optimal components, a singular spectrum decomposition method based on kurtosis optimization is proposed. First, the bearing vibration signal is subjected to decomposition via Singular Spectrum Decomposition, which yields a set of singular spectral components. Next, leveraging the high sensitivity of bearing fault characteristics to kurtosis, the kurtosis of each individual component is computed, and the component corresponding to the maximum kurtosis value is identified as the optimal one. Lastly, the chosen optimal component is subjected to envelope demodulation to extract the characteristic frequency, thereby enabling the completion of bearing fault diagnosis. The experimental results show that the proposed method can be very good for the bearing faults under strong background noise to complete the feature extraction.

2. Methodology

2.1 Singular Spectrum Decomposition

Singular Spectrum Decomposition (SSD) [2] is a signal decomposition method for dealing with nonlinear and nonsmoothed time series. This technique is based on the principle of matrix decomposition, which is able to disassemble a time series signal into several components with different frequencies and amplitudes. Specifically, the original signal is split into several subsequences and a singular value decomposition is performed for each subsequence to obtain the eigenvectors and corresponding eigenvalues in its subspace. Subsequently, these eigenvectors are sequentially arranged according to the magnitude of the eigenvalues to form a singularity spectrum, which consists of a series of orthogonal basis functions having different frequencies and amplitudes. Through the linear combination of these basis functions, the original time series signal can be recovered. This method is used in applications such as rolling bearing fault detection, as it helps to identify and analyze specific features and anomalies in the signal.

When dealing with the singular value selection problem, numerous researchers have proposed various strategies, including the singular value ratio spectrum method, the singular entropy method, and the singular value difference spectrum method. All of these methods are based on analyzing the singular value sequences and determining a suitable threshold to select the singular values based on different criteria. These methods show good noise reduction in signal processing with low signal-to-noise ratios, but may sacrifice some of the weak shock signal features in the noise, resulting in the absence of important periodic components in the reconstructed signal, which is a limitation in early mechanical fault diagnosis. In practice, these methods are often difficult to adapt to the diversity in engineering signals.

2.2 Kurtosis and its role in bearing fault diagnosis and analysis

Kurtosis is a statistical concept, which tells us how "sharp" or "flat" the distribution of a set of data. Simply put, it is to see how thick the tail of this set of data, or how prone to extreme values. If a distribution has a high crag, it means that it is more likely to have unusually large or small values than a normal distribution; if the crag is low, it means that it has a thin tail and extreme values are uncommon. This concept is particularly useful in areas such as financial risk assessment and signal processing, as it helps us understand the volatility and level of risk in our data. The calculation method of kurtosis is as shown in Eq. (1).

$$K = \frac{E(x-\mu)^4}{\delta^4} \tag{1}$$

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In bearing fault diagnosis, Kurtosis is an important statistical indicator that is sensitive to the characteristics of shock impulses generated during fatigue failures of bearing work surfaces. Since crag is particularly sensitive to large-value pulses in the signal, when early surface damage occurs in the bearing, periodic large-value pulses are generated in the vibration signal, and these pulses lead to a significant increase in the crag value. Therefore, by monitoring the change of the crag value, the early failure of the bearing can be effectively recognized, which provides an important basis for the assessment of the health state of the bearing and the early warning of the failure.

2.3 Technical route

The technical route of this paper is shown in Fig. 1

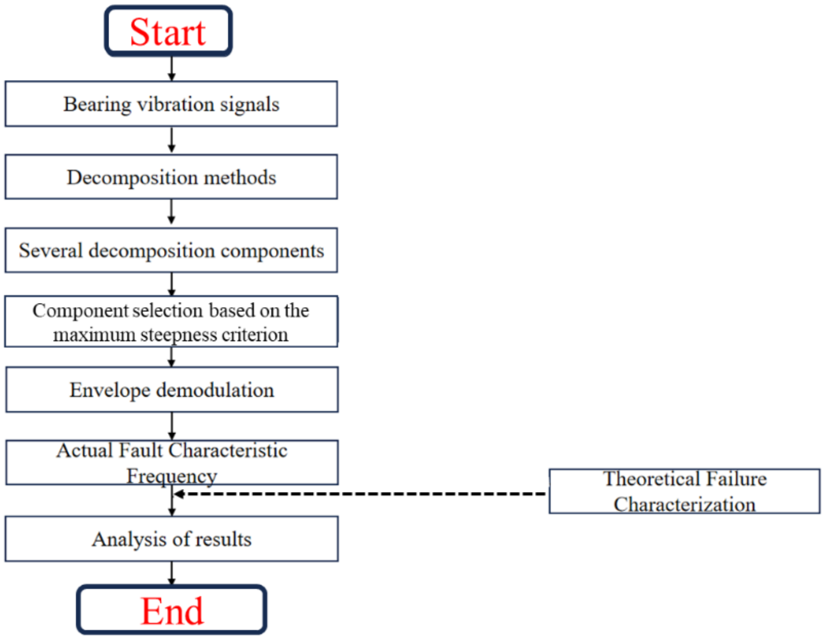

Fig.1 Overall flowchart of the proposed method

The specific steps are as follows:

(1) Collection of vibration signals for bearing faults

(2) Perform SSD decomposition on the bearing signals to obtain several singular spectrum components

(3) Calculate the kurtosis values of each component separately

(4) Select the optimal components based on the maximum kurtosis criterion

(5) Perform envelope demodulation on the optimal components

(6) Result analysis

3. Experimental Validation

3.1 Data introduction

In order to better simulate the actual engineering situation, the algorithm proposed in this paper is experimentally verified through the bearing failure data set provided by Case Western Reserve University (CWRU)[6].

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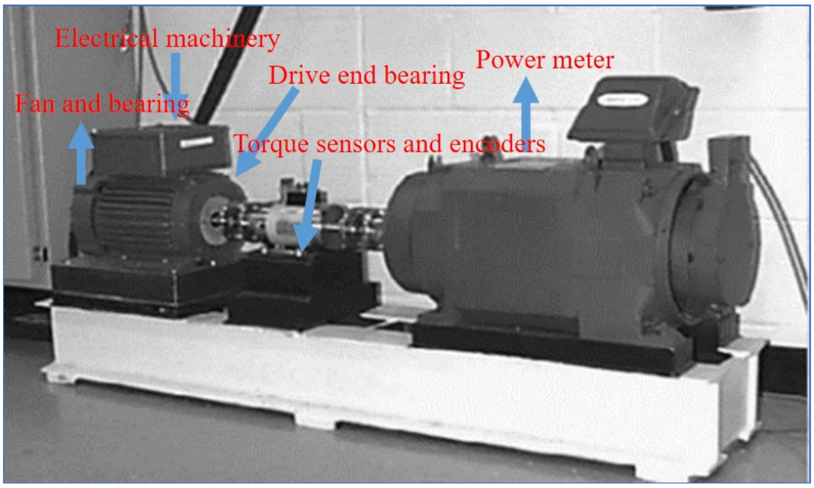

Fig.2 CWRU bearing failure test bench diagram

The bearing failure simulation test bench at is shown in Fig. 2. As can be seen in Fig. 2, the test bench mainly consists of a drive motor, drive-end bearing, fan-end bearing, torque sensor, encoder, and dynamometer. Among them, the deep groove ball bearings at the drive end of the motor are SKF-6205, and the bearing data are collected by acceleration sensors.

The method was analyzed using the outer ring data from the drive end, with a rotational speed of 1750 r/min and a sampling frequency of 12000Hz. Based on the calculation formula for the fault characteristic frequency of the outer ring of rolling bearings [5], it can be seen that the fault characteristic frequency is approximately 105Hz. In order to better simulate the strong background noise conditions at the engineering site, the -12dB Gaussian white noise was added to the original signal to increase the difficulty of signal analysis.

3.2 Experimental analysis

The time-domain waveform of the original signal is shown in Fig. 3. The time-domain waveform of the noisy signal is shown in Fig. 4. Analysis shows that the time-domain waveform components are disordered, with almost no impact information observable, and the overall background noise is significant. The envelope spectrum of the noisy signal is shown in Fig. 5. Analysis shows that it is difficult to observe effective components within the frequency band, and fault characteristic frequencies and frequency conversion information cannot be extracted. Therefore, noise reduction processing is required to improve the signal-to-noise ratio and enable the identification of fault characteristics.

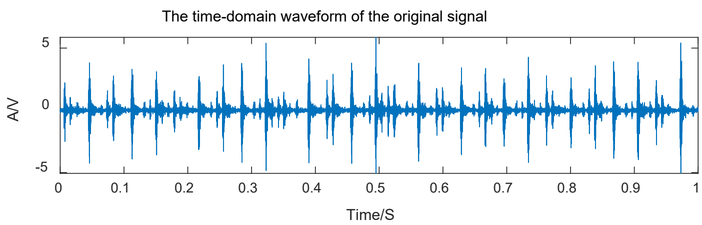

Fig.3 Time domain waveform diagram of the original signal

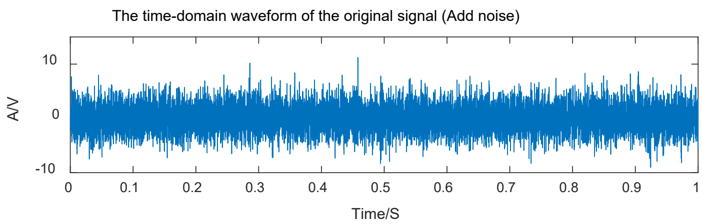

Fig.4 Time domain waveform diagram of the noisy signal

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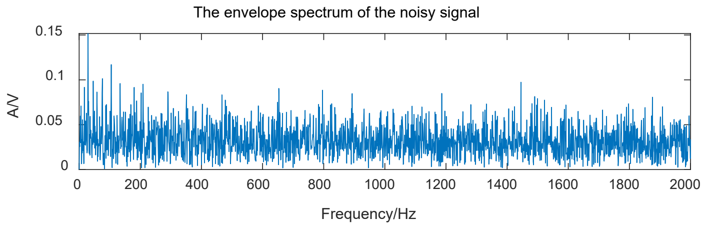

Fig.5 Envelope spectrum of noisy signal

Based on the above, the method described in this paper is used to analyze the noisy signal. First, the noisy signal is decomposed using SSD, as shown in Fig. 6. Analysis shows that after SSD decomposition, the original noisy signal is decomposed into 12 singular spectral components. Each component contains different information, and it is necessary to select the component with the richest fault feature information from the 12 components.

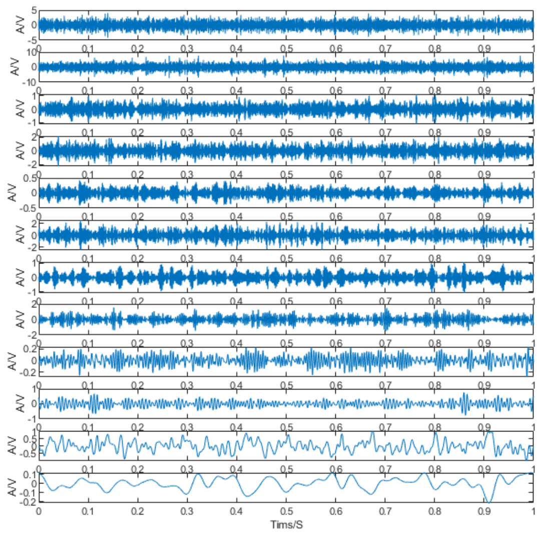

Fig.6 Decomposition component diagram of SSD

Based on the above, the components were screened using the kurtosis index. The kurtosis values of different components are shown in Fig. 7. Analysis shows that among the 12 components, the second component has the largest steepness value, which is 3.4401. Therefore, the second component is the best component.

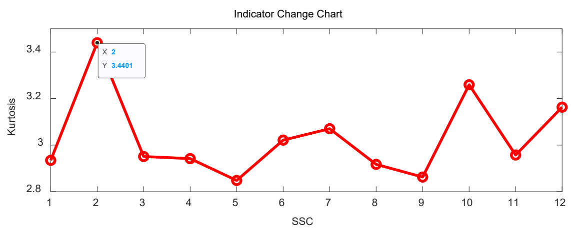

Fig.7 Kurtosis value diagram for different components

As can be seen from the above analysis, the second component is the optimal component, and its time-domain waveform is shown in Fig. 8. Analysis shows that the time-domain waveform of the optimal component can effectively observe periodic components. Comparing with Fig. 4, it can be seen that the proposed method can effectively reduce the interference of background noise and effectively extract periodic components related to faults under strong background noise. Furthermore, the envelope spectrum after envelope demodulation of the optimal component is shown in Fig. 9. Analysis shows that the envelope spectrum of the optimal component selected by the proposed method clearly reveals the fault characteristic frequency and transition frequency. The extracted fault characteristic frequency value is approximately 105Hz, which aligns with the theoretical value. The above results indicate that the

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proposed method can achieve good performance under strong background noise, enabling the extraction and identification of fault characteristics.

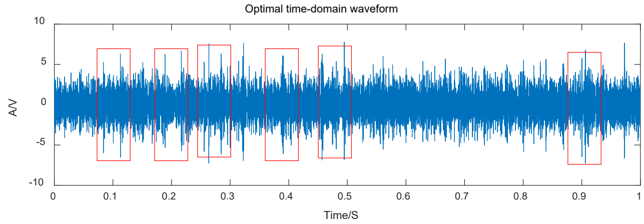

Fig.8 Time domain waveform diagram of noise reduction signal

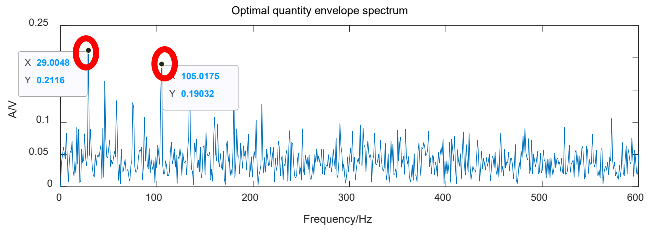

Fig.9 Envelope spectrum of noise reduction signal

To better highlight the effectiveness of the method described in this paper, Fig. 10 shows a comparison between the noisy signal and the optimal component envelope spectrum. Analysis shows that the optimal component envelope spectrum (Blue) obtained by the proposed method can effectively observe the fault characteristic frequency compared to the noisy signal envelope spectrum (Red). However, the noisy signal envelope spectrum is almost entirely noise components within the observable frequency band in the figure, making it difficult to perform fault discrimination.

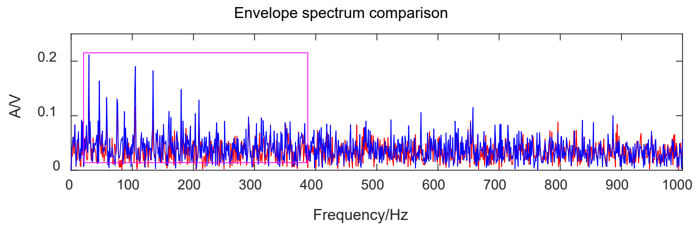

Fig.10 Comparison of the envelope spectra of the noisy signal and the denoised signal

In summary, the analysis of the above experimental results proves the effectiveness of the proposed method. The proposed method achieves the extraction of fault characteristic frequencies in strong background noise and the identification of fault characteristics, providing a new approach to bearing fault identification in engineering practice.

4. Conclusions

After SSD decomposition of the bearing fault signal, we evaluate each fault signal based on its kurtosis value and select the component that best represents the fault characteristics in the original signal. After selecting the optimal component, we further conducted envelope demodulation experimental results show that feature extraction by the above method can effectively and accurately complete the feature extraction of bearing faults in the presence of strong background noise. This method not only improves the accuracy of fault signal analysis, but also enhances the robustness to noise, which makes it possible to more reliably monitor and diagnose early bearing faults in practical applications, thus contributing to preventive maintenance and improving the operational efficiency of equipment.

Outlook: (1) The paper mainly relies on existing public datasets when validating the algorithm. In order to enhance the validity and reliability of the methodology, the subsequent research should design specific experiments to utilize the measured signals under actual working conditions for validation. In addition, applications in different environments and working conditions should be considered to ensure the universality and adaptability of the algorithm.

(2) In order to improve the accuracy and real-time performance of fault feature extraction, future

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research should be devoted to the development of more efficient models that can adaptively learn data features. Introducing deep learning network models is a direction worth exploring, as deep learning demonstrates significant advantages in handling complex patterns and improving prediction accuracy.

(3) In order to realize the comprehensiveness and accuracy of rolling bearing fault diagnosis, future research should explore the combination of vibration signal fault feature extraction techniques with other information fusion techniques. This includes, but is not limited to, temperature monitoring, sound analysis, image recognition, etc., in order to construct a multi-dimensional and multi-level fault diagnosis system, so as to more comprehensively characterize the operating state of the bearing and predict its life.

In summary, this paper argues that the future research direction focuses on improving the effectiveness, accuracy and real-time performance of the algorithms, as well as constructing a multi-information fusion fault diagnosis system to realize a more precise, comprehensive and real-time fault diagnosis of rolling bearings.

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