

A Review of Rolling Bearing Fault Diagnosis Methods based on Empirical Mode Decomposition

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Abstract

Empirical Mode Decomposition (EMD) has unique advantages in processing nonlinear and non-stationary signals due to its adaptability, and has been widely applied in the research on fault diagnosis of rolling bearings. This paper systematically combs the relevant literatures in this field in the past five years. From the perspective of the evolution of methods, the research has experienced a gradual deepening process from a single decomposition method to the fusion of multiple technologies and from traditional machine learning to deep learning integration. The existing research mainly focuses on three directions: improvement of decomposition algorithms, enhancement of noise suppression, and construction of intelligent recognition models, and has achieved remarkable progress in diagnostic accuracy and robustness. Analysis shows that the current research still has problems such as the disconnection between laboratory data and industrial practice, insufficient adaptability to complex working conditions, and lack of model interpretability. Future research needs to further focus on the design of lightweight algorithms, the improvement of cross-domain adaptability, and the fusion path of physical knowledge and data-driven methods.

Keywords

Empirical Mode Decomposition, Rolling Bearing, Fault Diagnosis.

1. Introduction

As the core component of rotating machinery, rolling bearings play an irreplaceable role in industrial production. The operating state of wind turbines, high-speed trains, coal mine fans and aero-engines is directly related to the safety and stability of the whole set of equipment. Once a bearing fails, it may cause production line shutdown at the minimum, and even serious safety accidents at the worst. Therefore, timely and accurate fault diagnosis of rolling bearings is not only an important link in equipment maintenance and management, but also a practical demand to ensure the continuity and safety of industrial production. However, bearing vibration signals under actual working conditions often show obvious nonlinear and non-stationary characteristics, with complex background noise and weak early fault features, which bring great challenges to traditional signal processing methods.

The proposal of the Empirical Mode Decomposition method provides a new idea for solving the above problems. Different from the traditional Fourier transform or wavelet analysis, Empirical Mode Decomposition can adaptively decompose a signal into several Intrinsic Mode Functions (IMFs) according to the signal's own time-scale characteristics without predefining basis functions, and this data-driven characteristic endows it with unique advantages in processing nonlinear and non-stationary signals. In recent years, this method has been widely applied in the field of rolling bearing fault diagnosis, and many scholars have carried out a lot of research on its theoretical basis, improved algorithms and integrated application with other technologies. From simple signal decomposition and envelope spectrum analysis, to combination with signal processing technologies such as Independent Component Analysis

(ICA) and Singular Value Decomposition (SVD), and then to deep integration with machine learning algorithms such as Support Vector Machine (SVM) and Probabilistic Neural Network (PNN) and even deep learning models such as Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) network, the research on diagnosis methods based on Empirical Mode Decomposition has shown a prosperous development trend.

Combing the existing literatures, it can be found that researchers have made remarkable progress in improving diagnostic accuracy, enhancing anti-noise ability and improving model interpretability. Some studies focus on the improvement of the decomposition algorithm itself, such as proposing variants such as Complete Ensemble Empirical Mode Decomposition (CEEMD), Improved Complete Ensemble Empirical Mode Decomposition (ICEEMD) and Time-Varying Filtering Empirical Mode Decomposition (TVF-EMD) to overcome the mode mixing problem in the original algorithm. Some studies are committed to combining Empirical Mode Decomposition with various noise reduction technologies, and extract clear fault features under the background of strong noise by optimizing threshold functions or introducing intelligent optimization algorithms to screen effective components. Other scholars have tried to convert the signals processed by Empirical Mode Decomposition into two-dimensional images, and realize end-to-end fault recognition with the powerful feature extraction capability of deep learning. Such methods have outstanding performance in the diagnosis of complex faults, especially compound faults. These studies have promoted the development of this field from different perspectives, but at the same time, the research results in this direction are relatively scattered and lack systematic induction and combing.

This literature review aims to systematically sort out the research progress of fault diagnosis methods for rolling bearings based on Empirical Mode Decomposition in the past five years, and focus on analyzing the core ideas, technical routes and applicable scenarios of various methods. By summarizing and comparing the relevant studies, this paper reveals the main trends and hot directions of the current research, identifies the advantages and disadvantages of the existing methods, thus providing a clear reference framework for subsequent research. The time scope of the review is mainly from 2022 to 2025, and the literature types are mainly domestic and foreign journal papers and conference papers, which basically reflect the latest research results and development trends in this field in recent years. By sorting out and analyzing these literatures, it is hoped to help researchers quickly grasp the research context of this field, clarify the possible research entry points in the future, and lay a foundation for further exploring more efficient and reliable bearing fault diagnosis methods.

2. Literature Review and Analysis

2.1. EMD-Based Fault Feature Extraction for Rolling Bearings

The Empirical Mode Decomposition method is widely used in the field of rolling bearing fault diagnosis due to its ability to adaptively process nonlinear and non-stationary signals. Aiming at the problem of strong non-stationarity of bearing vibration signals, Li Ning reduced the randomness by performing difference operation on the signal sequence, and combined with the Empirical Mode Decomposition method to perform multi-scale decomposition on the signal, so as to obtain Intrinsic Mode Functions with relatively single frequency[1]. On this basis, the Hilbert transform is used to extract the bearing fault features, realizing the effective identification of fault frequency information. Lv Zuopeng et al. combined Empirical Mode Decomposition with wavelet packet analysis and Hilbert-Huang Transform (HHT), constructed a vibration signal analysis method suitable for high-speed bearings of aero-test rigs, realized noise suppression through wavelet packet, and then obtained fault characteristic frequencies through EMD decomposition and HHT time-frequency analysis[2]. The research results show that this method can effectively extract bearing fault information under complex working

conditions. Aiming at the problem that the early weak fault signals of bearings are difficult to identify, Bao Huaiqian et al. proposed a diagnostic model combining Empirical Mode Decomposition with convolutional sparse filtering, reconstructed the signal by selecting IMF components with large kurtosis, and enhanced the fault feature expression ability by sparse feature learning[3]. The experimental results show that this method has good performance in anti-noise ability and feature recognition. Chen Long et al. used Empirical Mode Decomposition to obtain multiple Intrinsic Mode Functions, extracted time-domain and frequency-domain features through envelope spectrum analysis, then adopted Principal Component Analysis (PCA) to reduce the feature dimension, and combined with Probabilistic Neural Network to realize bearing state recognition[4]. The experimental results show that this method has good interpretability and high recognition accuracy. From the perspective of feature extraction efficiency, Yu Yongjun et al. screened the main modes by calculating the energy proportion of each IMF component, combined them with the time-domain features of the original signal, then used Principal Component Analysis to extract key features, and finally realized fault classification through BP neural network. The experimental results show that this method improves the fault diagnosis accuracy while maintaining low computational complexity[5]. On the basis of traditional EMD, Morgan et al. proposed the SSA-IWT-EMD method, optimized the noise reduction parameters by improving the wavelet threshold function and sparrow search algorithm, and then selected IMF components for signal reconstruction by using comprehensive indicators[6]. The research shows that this method is superior to traditional methods in noise suppression and feature extraction. Lei Chunli et al. also proposed the SSA-IWT-EMD fault diagnosis method for rolling bearings, improved the threshold function and optimized the parameters by using the sparrow search algorithm, which made the signal noise reduction effect more obvious and further improved the application effect of EMD in fault feature extraction[7]. Relevant studies show that Empirical Mode Decomposition can effectively decompose complex vibration signals and play an important role in fault feature extraction, but it still needs to be combined with other methods to improve the analysis performance in noisy environments.

Signal decomposition methods are mainly used to extract IMF components and further analyze fault features in bearing fault diagnosis. Different studies optimize the EMD results by introducing wavelet analysis, envelope spectrum analysis or statistical indicators to enhance the feature recognition ability. Relevant studies provide an important technical foundation for the processing of non-stationary vibration signals in complex mechanical systems.

2.2. EMD-Based Fault Diagnosis Using Intelligent Algorithms

With the development of intelligent algorithms, combining Empirical Mode Decomposition with machine learning or intelligent optimization algorithms has gradually become an important research direction in bearing fault diagnosis. Gao Yunfeng and Zhang Jinping proposed a fault feature extraction method based on EMD and FastICA, decomposed the vibration signal into multiple modal components by EMD, screened effective IMFs according to the correlation coefficient, and then used FastICA to separate the source signal from the noise signal, thus obtaining clearer fault characteristic frequencies[8]. On this basis, Ma Weiping et al. further proposed the ICEEMD-FastICA joint diagnosis method, obtained IMF components through Improved Complete Ensemble Empirical Mode Decomposition, reconstructed them by using the kurtosis criterion, and then combined with FastICA for signal noise reduction and separation[9]. The experimental results show that this method improves the signal-to-noise ratio by 29.54% compared with traditional methods and can identify bearing fault features more accurately. Wu Binmei et al. combined EMD with Singular Value Decomposition and KNN classification method, realized bearing fault recognition through multi-domain feature extraction and PCA dimensionality reduction, and improved the recognition efficiency of the

diagnostic model[10]. Zhang Yanjun and Yang Bo proposed a diagnostic method combining EMD with SSA-optimized SVM, obtained IMF components through EMD decomposition and extracted envelope spectrum features, then optimized SVM parameters by using the sparrow algorithm, thus realizing the accurate identification of different fault types of bearings[11]. Aiming at the problem of complex operating environment of rolling bearings of coal mine main fans, Li Tao et al. adopted CEEMD to decompose the vibration signal, calculated the IMF sample entropy and singular value spectrum features, then combined with PNN network to construct a fault diagnosis model, and improved the model recognition accuracy through an adaptive weight adjustment mechanism[12]. From the perspective of diagnostic interpretability, Jing zhi and Zhang Chunlong combined EMD with the classifier ensemble method, constructed a rule-based classifier and adopted a voting mechanism for comprehensive decision-making, making the diagnostic process closer to the reasoning process of technicians[13]. The experimental results show that this method can achieve a recognition accuracy of 90% under various rotational speed conditions. Relevant studies show that the introduction of machine learning algorithms and optimization algorithms can effectively improve the diagnostic performance of EMD in complex signal environments and enhance the intelligence and stability of the model.

2.3. Intelligent Fault Diagnosis of Rolling Bearings Using EMD and Deep Learning

The development of deep learning technology has promoted the evolution of rolling bearing fault diagnosis towards intelligence. Zhao Guowei and Zeng Jing proposed a diagnostic method based on EMD-GAF and improved SERE-DenseNet, converted the one-dimensional signal into a two-dimensional image by the GAF method after EMD decomposition and reconstruction of the vibration signal, and then performed feature extraction and fault classification through the improved DenseNet network[14]. The experimental results show that the average diagnostic accuracy of this method on the CWRU dataset reaches 99.91%. Zhao Fukai et al. combined EMD with a multi-channel convolutional neural network, screened IMF components by kurtosis and correlation coefficient weighting and constructed a multi-channel input dataset, then used the convolutional neural network for fault recognition[15]. The experimental results show that this method has high recognition accuracy and good generalization ability under different signal-to-noise ratio conditions. Shang Shua et al. proposed a fault diagnosis technology based on the combination of EMD and CNN-LSTM, denoised and reconstructed the vibration signal by EMD, and then input the processed signal into the CNN-LSTM model for automatic feature learning and fault classification[16]. The experimental results on the CWRU dataset show that the classification accuracy of the model can reach 99.20%. Ahmed Chennana et al. proposed a method combining EMD with the Minimum Entropy Deconvolution Adjusted (MEDA) algorithm, obtained IMF components by EMD and performed MEDA processing on the reconstructed signal to enhance the fault impact features[17]. The experimental results prove that this method can effectively improve the ability to identify fault information in vibration signals. Based on TVF-EMD, Chang Binjie and Cui Ruimin proposed a new fault diagnosis method, screened IMF components by kurtosis and extracted energy features by envelope entropy, then adopted the random forest model for classification and prediction[18]. The experimental results show that its diagnostic accuracy reaches 99.5%. Shi Qiongyan and Yang Fengbo proposed the EMD-AADPCI vibration image generation method and constructed a CNN-LSTM hybrid model to realize complex fault diagnosis, mapped IMF features into polar coordinate vibration images and combined with deep network for feature extraction[19]. The experimental results show that this method has high accuracy and good anti-noise performance in compound fault diagnosis. Deep learning models can improve fault recognition accuracy through automatic feature learning. Combined with EMD, they can not only effectively extract

multi-scale features in vibration signals, but also improve the diagnostic ability under complex working conditions, providing a new research direction for the intelligent fault diagnosis of rolling bearings.

3. Review and Prospects

Despite the fruitful research results in this field, there are still some problems worthy of in-depth consideration. Most of the existing methods verify their effectiveness on specific datasets, mainly the public dataset of Case Western Reserve University (CWRU). These data are collected from laboratory environments with single fault types and relatively stable working conditions, which are quite different from the complex and changeable operating conditions of actual industrial sites. Although many studies claim that the methods have good robustness, their anti-noise performance tests are often limited to adding Gaussian white noise with a specific signal-to-noise ratio, and the adaptability to complex working conditions such as actual non-Gaussian noise, pulse interference, variable rotational speed and variable load lacks sufficient verification. Empirical Mode Decomposition and its improved algorithms generally have high computational complexity, and it is difficult to guarantee real-time performance when processing long-sequence data, which restricts the application of online monitoring and real-time diagnosis. Another problem that cannot be ignored is that a large number of studies focus on improving the diagnostic accuracy but ignore the interpretability of the model, which is particularly obvious in deep learning methods. This black-box characteristic makes it difficult for technicians to understand the basis of diagnostic results, which affects the acceptance and trust of the methods in actual sites to a certain extent.

From the perspective of research trends, the development of this field may deepen in several directions in the future. Lightweight and real-time performance will become important considerations for algorithm improvement. How to reduce computational complexity and improve processing speed while ensuring diagnostic accuracy to adapt to the needs of edge computing and embedded systems is a problem that needs to be focused on. The research on cross-domain adaptability also needs to be strengthened. Developing feature extraction and diagnosis methods that can adapt to different working conditions, different equipment and even different data distributions and improving the generalization ability of the model are of great significance for promoting the transformation of research results from laboratory to practical application. Compound fault decoupling and weak feature enhancement are still technical difficulties. When a bearing has multiple faults at the same time or early fault features are submerged by strong noise, there is still much room for improvement in the diagnostic ability of existing methods. The fusion of physical knowledge and data-driven methods is also worthy of attention. Integrating prior knowledge such as bearing fault mechanism and dynamic model into the deep learning framework can not only improve the diagnostic performance, but also help to improve the interpretability of the model. This fusion idea may be one of the effective ways to break through the current research bottleneck.

4. Conclusion

From the perspective of existing literatures, the research on fault diagnosis of rolling bearings based on Empirical Mode Decomposition has formed a relatively complete technical system. Early studies mainly focused on verifying the applicability of Empirical Mode Decomposition itself in bearing signal processing, and extracted fault characteristic frequencies by direct Hilbert envelope spectrum analysis after decomposition. With the deepening of research, scholars have gradually realized the inherent limitations of the original Empirical Mode Decomposition such as mode mixing and end effect, and thus successively proposed various improved versions such as Ensemble Empirical Mode Decomposition (EEMD),

Complementary Ensemble Empirical Mode Decomposition (CEEMD), Complete Ensemble Empirical Mode Decomposition (CEEMD) and Improved Complete Ensemble Empirical Mode Decomposition (ICEEMD). These methods have suppressed the mode mixing phenomenon to a certain extent and improved the stability of decomposition by adding auxiliary noise or optimizing iteration strategies. In recent years, the emergence of new variants such as Time-Varying Filtering Empirical Mode Decomposition has further enriched the family of Empirical Mode Decomposition methods and provided more options for processing non-stationary signals.

At the technical fusion level, Empirical Mode Decomposition has transcended the role of a simple signal processing tool and gradually evolved into a basic module in the fault diagnosis framework. Some researchers are committed to combining Empirical Mode Decomposition with various signal processing technologies, such as combining with Independent Component Analysis and its improved algorithms to construct noise channels for source signal separation, matching with Minimum Entropy Deconvolution or Minimum Entropy Deconvolution Adjusted technology to enhance fault features, and combining with wavelet packet or wavelet threshold function to realize collaborative noise reduction. Other researchers focus on the pattern recognition link after feature extraction, combine Empirical Mode Decomposition with traditional machine learning algorithms such as Support Vector Machine, Probabilistic Neural Network and random forest, and perform fault recognition by extracting statistical features such as energy, entropy and kurtosis of Intrinsic Mode Components and inputting them into the classifier. It is worth noting that the rise of deep learning technology has injected new vitality into this field. The method of combining Empirical Mode Decomposition with Convolutional Neural Network, Long Short-Term Memory network and their variants has become a research hotspot in recent years. Such methods often convert the signals processed by Empirical Mode Decomposition into two-dimensional images or sequence data, use the powerful automatic feature extraction capability of deep networks to complete end-to-end fault diagnosis, and show superior performance in complex working conditions and compound fault scenarios.

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