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Fault Diagnosis of Strong Noise in Rolling Bearings based on EEMD-RRSD

Shibin Chen [a], Hanjun Jiang *, Wenqiang Han, Chengyu Liu

School of Qingdao Technological university, Qingdao 266520, China
[a] 550067570@qq.com
*Corresponding author

ABSTRACT

Rolling bearings often operate under complex working conditions. When local faults occur in rolling bearings, their vibration signals contain not only periodic transient shock components related to fault information, but also harmonic components such as shaft rotation frequency and background noise. Therefore, bearings operate in high noise fault environments, and direct envelope demodulation analysis of rolling bearing vibration signals often yields poor results. A strong noise fault diagnosis method for rolling bearings based on EEMD-RRSD is proposed to address the above issues. This method first performs EEMD decomposition on the signal, and then reconstructs the signal based on spectral kurtosis and correlation coefficient criteria. Perform resonance sparse decomposition on the reconstructed signal, perform Hilbert demodulation analysis on the low resonance components based on the fast spectral kurtosis map, extract the characteristic frequency of bearing faults, and then diagnose rolling bearing faults. The analysis results of simulation signals and experimental signals show that this method can effectively extract the impact components in the vibration signals of bearing faults and diagnose bearing faults.

KEYWORDS

Rolling Bearings; Fault Diagnosis; Resonance Coefficient Decomposition; EEMD.

1. INTRODUCTION

Vibration signals have nonlinearity and non stationarity, and feature information of vibration signals needs to be extracted before fault diagnosis. Signal decomposition decomposes the original vibration signal into modal components of different frequency bands, which is beneficial for uncovering hidden information in the vibration signal[1].. Most commonly used signal decomposition methods are based on the idea of modal decomposition, such as （Variational Mode Decomposition, VMD) [2], (Empirical Mode Decomposition, EMD) [3], (Ensemble Empirical Mode Decomposition ,EEMD) [4] and others. In order to improve the diagnostic accuracy of composite faults in rolling bearings, Wang et al. proposed a new algorithm for separating composite faults based on ensemble empirical mode decomposition and ICA [5]. This method effectively separates composite faults by executing ICA Yu et al. first applied RSSD to the field of mechanical fault diagnosis and proposed an envelope analysis method based on RSSD [6]. This method decomposes the vibration signal into different components through RSSD and performs envelope analysis on the low resonance components containing bearing fault information, successfully detecting faults in the inner and outer rings of the rolling bearing. Chen et al. proposed a diagnostic method that combines adaptive RSSD and WT[7], using the kurtosis of low resonance components as the fitness function of the genetic algorithm to select the optimal quality factor. Then, based on the energy distribution, the main sideband is selected to reconstruct the low resonance components, ultimately extracting the fault characteristics of the bearing. Based on previous research, this article adopts the EEMD-RRSD algorithm to solve the fault diagnosis problem of raceway bearings under strong noise operation.

2. BASIC PRINCIPLE

2.1. EEMD Algorithm

The EMD algorithm decomposes and reassembles time-domain signals into a series of IMF components and a residual. EEMD introduces Gaussian white noise with uniform frequency distribution based on the EMD algorithm, reducing the problem of mode mixing between components caused by signal complexity in EMD. Please refer to the literature for specific steps[4].

2.2. RSSD Algorithm

Resonance Sparse Decomposition (RSSD) uses the resonance properties of a signal as the basis for decomposition, and then separates high and low resonance components through morphological component analysis, represented as

$$\mathrm{y}=S_1W_1+S_2W_2+n \tag{1}$$

In the formula, S1 and S2 are the basis function libraries generated by high and low quality factors, respectively; W1 and W2 are the coefficient matrices of their corresponding components; N is the residual component.

This method achieves signal decomposition through the dual channel decomposition filter bank shown in Figure 1. Hh (ω) and H1 (ω) are high and low-pass filters, where (low pass scaling, LPS) α and (high pass scaling, HPS) β are obtained from equation (2)

$$\beta=\frac{2}{Q+1},\alpha=1-\frac{\beta}{r} \tag{2}$$

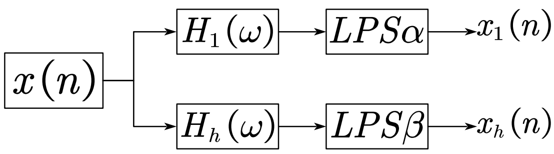


Fig 1. Block diagram of two-channel decomposition filter banks

Firstly, select appropriate high and low quality factors Q_h and Q_L, redundancy factors, and decomposition levels to obtain the corresponding wavelet basis function libraries S1 and S2. Then, through Q-switching and wavelet transform, obtain the initial coefficient matrix of the corresponding sub-band, and generate the initial high resonance components S1W1 and S2W2. Then select appropriate weight coefficients to establish the dissipation function formula (3), and use the split augmented Lagrangian contraction algorithm to obtain the optimal coefficient matrices W1* and W2*with the minimum dissipation function. The sparse expressions of high and low resonance components in the original signal are finally reconstructed as S1W1* and S2W2 *.

$$J(W_1,W_2)=\left\|x-S_1W_1-S_2W_2\right\|_2^2+\lambda_1\left\|W_1\right\|_1++\lambda_2\left\|W_2\right\|_1 \tag{3}$$

The technical flowchart of this article is shown in Figure 2.

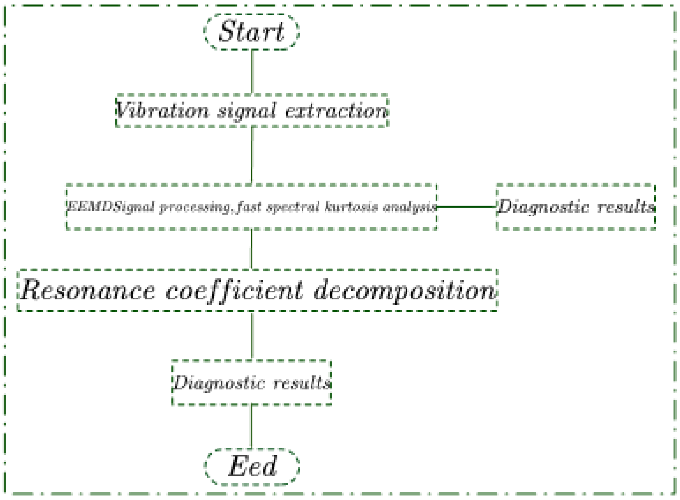


Fig 2. The technical flowchart of this article

3. EXPERIMENTS AND DATA ANALYSIS

3.1. Jiangnan University Bearing Dataset

To verify the effectiveness of the algorithm in actual bearing fault diagnosis, the bearing dataset from Jiangnan University was used for validation. The experiment used N205 and NU205 bearings, with an acceleration sensor sampling frequency of 50 kHz. The bearing parameters are shown in Table 1.

Table 1. Bearing information for verification

Contents	N205	NU205
Bearing outer diameter	52 mm	52 mm
Bearing inner diameter	25 mm	25 mm
Bearing width	15 mm	15 mm
Bearing roller diameter	7 mm	7 mm
The number of the rollers	10	11
Contact angle	0 rad	0 rad
Outer-race defect(width × depth)	0.3 × 0.25 mm Early stage	
Rolling element defect (width × depth)	0.5 × 0.15 mm Early stage	
Inner-race defect (width × depth)		0.3 × 0.25 mm Early stage

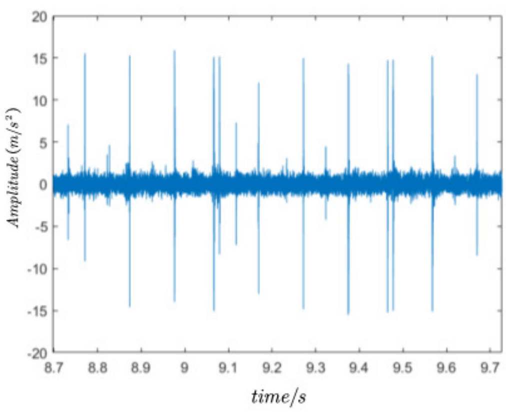


Fig 3. Original signal time --domain waveform

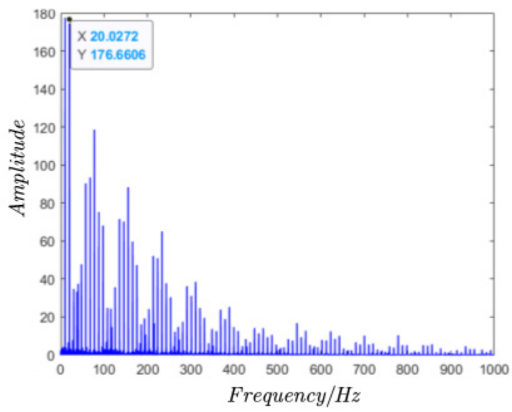


Fig 4. Envelope spectrum

The experiment was conducted at three different speeds of 600 r/min, 800 r/min, and 1000 r/min, each with four types of bearing faults. Taking the outer ring fault data of a bearing under operating conditions of 600 r/min as an example, the characteristic frequency of the outer ring fault bearing is calculated according to formula (8) as fouter=77.45 Hz.

$$f_{outer} = \frac{N}{2} n(1 - \frac{d}{D} \cos\phi) \tag{4}$$

The original signal is shown in Figure 3, and the envelope spectrum analysis is shown in Figure 4 It can be seen that the fault characteristic harmonics are masked and not obvious.

3.2. EEMD Decomposition and Reconstruction

This article takes the vibration signal of bearing outer ring fault as an example to decompose and reconstruct the signal of bearing outer ring fault vibration signal using EEMD. The components of the outer ring fault of the bearing after EEMD decomposition are shown in the figure 5a. Select the first 5 IMF components in Figure 5 for analysis. Calculate the kurtosis values and correlation coefficients of each IMF component, and obtain the kurtosis values of each IMF component as listed in Table 2.

Table 2. Correlation coefficient and kurtosis value

MF Serial Number	1	2	3	4	5
correlation coefficient	0.8272	0.2300	0.2038	0.2428	0.2757
kurtosis value	146.8720	15.2910	8.9009	2.7802	3.5033

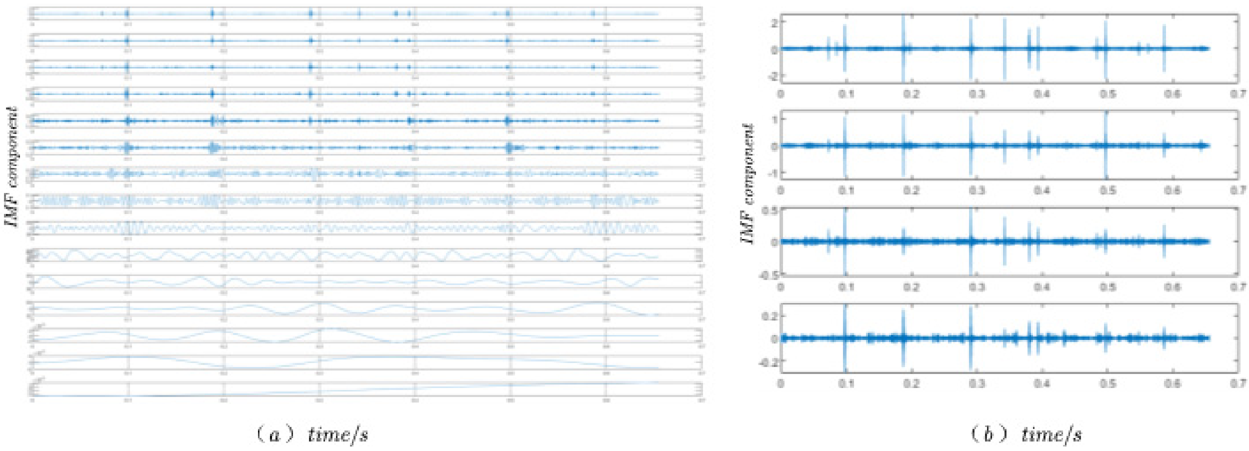


Fig 5. Time domain waveform

Select the first 5 IMF components in Figure 5 for analysis. Calculate the kurtosis value and correlation coefficient of each IMF component, and obtain the reconstructed signal according to the kurtosis value and correlation coefficient criteria. As shown in Figure 5b. Perform envelope spectrum analysis on the reconstructed signal as shown in Figure 7 It can be seen that signal interference is effectively reduced, but the fault characteristic harmonics are still masked.

3.3. Resonance Sparse Decomposition

Perform resonance sparse decomposition method on the reconstructed signal to obtain high and low resonance components. Based on the fast spectral kurtosis diagram 11, select the low resonance component in Figure 6 as the research object. By analyzing the envelope spectrum of the low resonance component, it can be seen from Figure 8 that the harmonics are prominent.

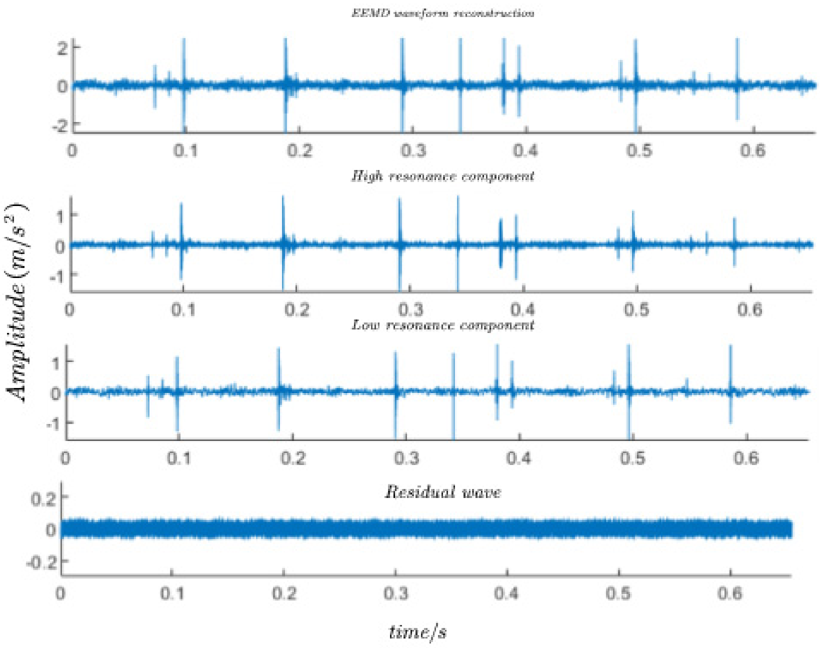


Fig 6. Time domain waveform

3.4. Simulation Analysis

To verify the effectiveness of the proposed method in this paper, a numerical simulation model of rolling bearings was used to simulate the outer ring fault of rolling bearings. The numerical simulation model is represented as

$$\begin{cases} x(t) = s(t) + n(t) \\ s(t) = \sum_{j} h(t - j \times T - \tau_i) + p(t + t_1) + p(t + t_2) \\ h(t) = A_o esp(-Ct)\cos(2\pi f_n t) \\ p(t) = M_o esp(-Dt)\cos(2\pi f_m t) \end{cases} \tag{5}$$

In the formula, the simulated signal x(t) contains transient impulse signals that occur cyclically s(t) and noise signal n(t).

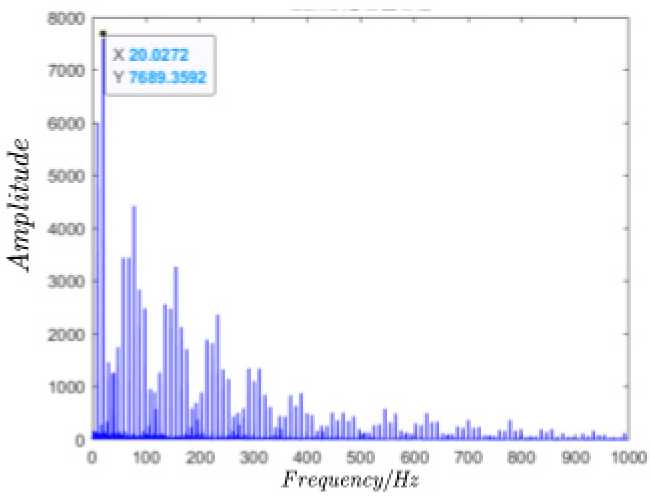


Fig 7. EEMD envelope spectrum

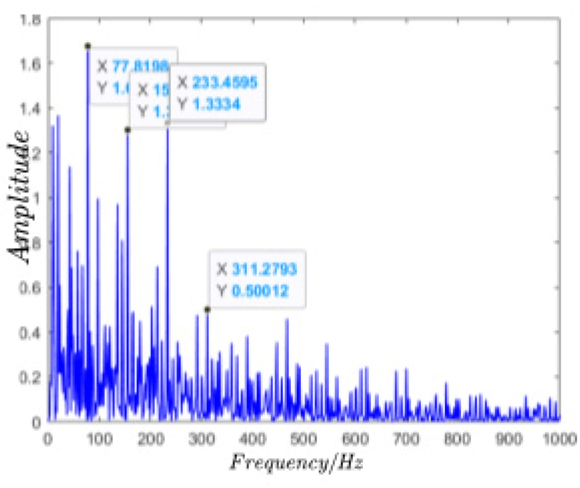
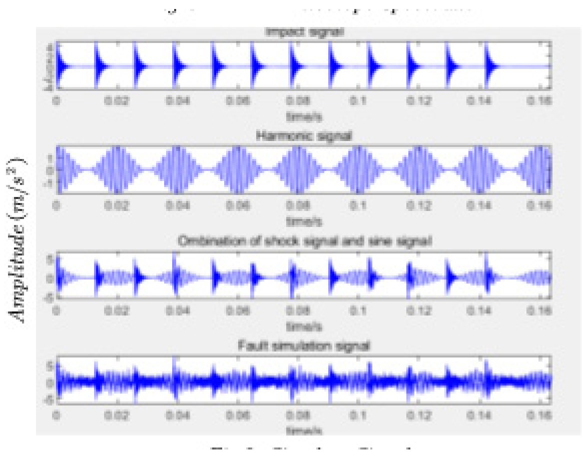


Fig 8. Low resonance component envelope spectrum



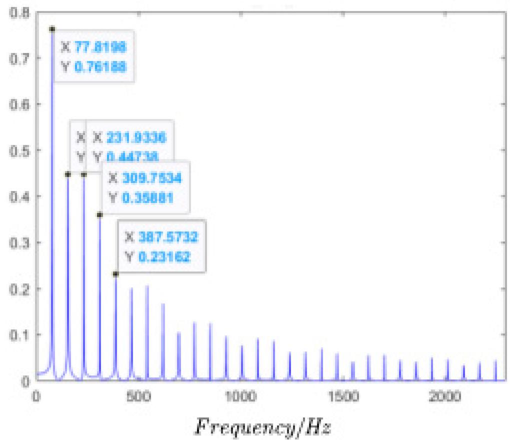


Fig 9. Simulate signal **Fig 10.** Simulation signal envelope spectrum

A set of simulated signals is shown in Figure 7. Perform envelope processing on the signal to obtain the fault characteristic frequency. The error between simulation and experimental data should not exceed 1% to verify the correctness of the algorithm model.

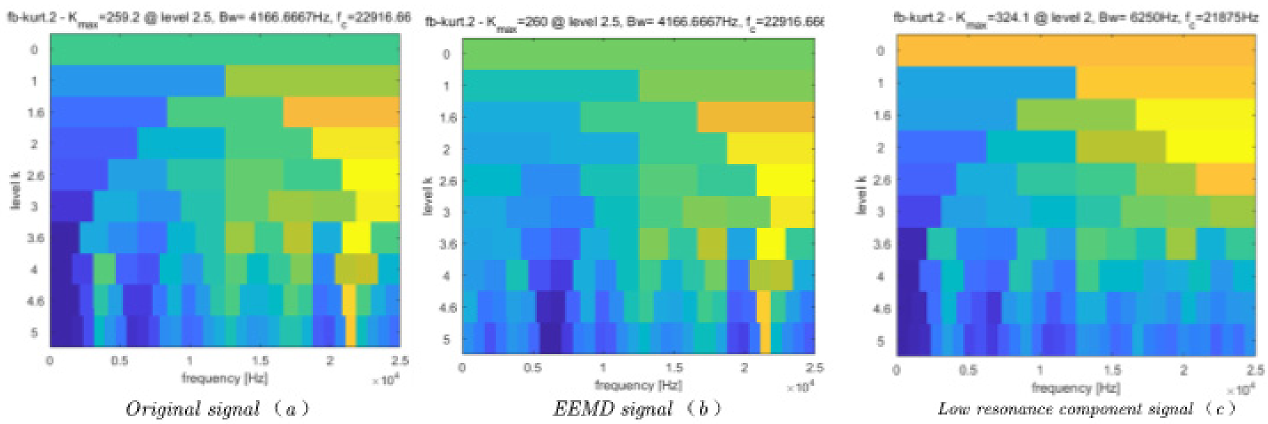


Fig 11. Fast spectral kurtosis

4. CONCLUSION

This article proposes a fault diagnosis method for vibration signals based on EEM-RSSD, and draws the following conclusions through experimental results and analysis. (1) Due to the presence of a large amount of interfering noise signals in the acoustic vibration signals of bearings during faults, the decomposition and reconstruction method based on EEMD can effectively enhance the useful information of bearing fault vibration signals and highlight the fault characteristic frequencies of bearings. (2) EEMD decomposes and processes the original signal to obtain the kurtosis values and correlation coefficients of several IMF components. The kurtosis values and correlation coefficients can effectively reflect the characteristics and fault information of the original signal. (3) EEMD-RRSD processing of signals can effectively obtain the characteristic frequency of fault signals, and the effectiveness of the algorithm has been verified through simulation

REFERENCES

[1] Yang H, Li L, Li G, et al. A Novel Feature Extraction Method for Ship-Radiated Noise[J]. Defence Technology, 2022, 18(4): 604-617.

[2] Dragomiretskiy K, Zosso D. Variational Mode Decomposition[J]. IEEE Transactions on Signal Processing, 2014, 62(3): 531-544.

[3] Huang N E, Shen Z, Long S R, et al. The Empirical Mode Decomposition and the Hilbert Spectrum for Nonlinear and Non-stationary Time Series Analysis[J].Proceedings of the Royal Society A, 1998, 454: 903-995.

[4] Wu Z, Huang N E. Ensemble Empirical Mode Decomposition: a Noise-Assisted Data Analysis Method[J]. Advances in Adaptive Data Analysis, 2009, 1(01): 1-41.

[5] Wang H, Li R, Tang G, et al. A Compound Fault Diagnosis for Rolling Bearings Method Based on Blind Source Separation and Ensemble Empirical Mode Decomposition[J]. Plos One, 2014,9(10): e109166.

[6] Chen X M, Yu D J, Luo J S. Envelope demodulation method based on resonance-based sparse signal decomposition and its application in roller bearing fault diagnosis[J]. Journal of Vibration Engineering, 2012, 25(6): 628-636.

[7] Chen B, Shen B, Chen F, et al. Fault diagnosis method based on integration of RSSD and wavelet transform to rolling bearing[J]. Measurement, 2019, 131: 400-411.