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Rolling bearing fault diagnosis method based on EWT-MED

Zhenxiong Wu [a], Linjun Wang [b], Tengxiao Zou [c]

Hubei key Laboratory of Hydroelectric Machinery Design and Maintenance, College of Mechanical and Power Engineering, China Three Gorges University, Yichang, Hubei 443002, P. R. China;

[a]982366375@qq.com, [b]ljwang2006@126.com, [c]1963731883@qq.com

Abstract

Aiming at the problem that bearing fault features are difficult to extract, this paper proposes a rolling bearing fault feature extraction method based on Empirical Wavelet Transform (EWT) and minimum entropy convolution (MED). Firstly, we use EWT to reduce the noise of the original signal, and use the relevant steepness criterion to screen out the components with high noise content and low noise, and then filter the components with high noise content to reduce the interference of pulse fault signals. Finally, the signal after noise reduction is superimposed with the signal with low noise content and the envelope spectrum analysis is performed. The experimental results show that the proposed method can effectively extract the fault characteristics and reduce the noise interference.

Keywords

Empirical Wavelet Transform; Minimum Entropy Convolution; Steepness; Correlation.

1. Introduction

Rolling bearings are important parts of mechanical equipment, and due to their long-term load and harsh environment, they cannot guarantee the stability of operation. Rolling bearing fault signals are usually collected and contain noise signals, and the type of fault cannot be accurately and quickly determined using a single analysis method. Therefore, how to extract bearing fault characteristics from noise signals has become the main research content.

The vibration signal generated by the failure of rolling bearings is generally a nonlinear, non-cyclic and smooth high-frequency signal, which makes it difficult to extract the fault frequency. Common noise reduction methods include empirical mode decomposition[1], singular value decomposition[2], etc. Empirical modal decomposition adapts well, but has endpoint effects and modal aliasing. Singular value decomposition is simple, but the program takes a long time to run. The EWT[3], which automatically decomposes a signal into a finite number of MRA components based on signal characteristics, is particularly good at handling nonlinear and nonstationary signals. Sheng et al[4]. used the improved EWT for the aero-engine rotor simulation tester, and the applicability and robustness were enhanced. Li [5] used the particle swarm optimization algorithm to optimize the step size in the MED to achieve better noise reduction effect. Endo et al.[6] combined with MED to amplify the fault characteristics, which is convenient for easier extraction of fault frequency, but the order of the filter will affect the extraction of fault frequency. Xu et al. [7] used the wavelet packet transform and EEMD methods to process the original signal. Due to the weak bearing fault characteristics, the fault signal in the background of strong noise will be drowned out by the noise, which seriously affects the fault feature extraction.

In order to accurately extract the fault characteristics, weaken the influence of noise, and enhance the fault signal impact characteristics. In this paper, MED is used to enhance the feature information in the fault band, and a fault feature extraction method for rolling bearings based on EWT and MED is proposed. Firstly, EWT is used to reduce the noise of bearing fault signals, and the relevant steepness screening criterion is used as the choice to determine MRAs that require subsequent noise reduction treatment. Secondly, MED is used to enhance the fault characteristics in the frequency band of denoising signal. Finally, the fault signal is enveloped and demodulated, and the characteristic frequency and high harmonics of the rolling bearing fault are accurately extracted.

2. EWT principle

EWT is a signal decomposition method proposed by Gilles in 2013[8], which combines the complete theory of wavelet transform and the advantages of EMD multilayer decomposition to achieve the modal decomposition by setting a wavelet filter in the Fourier spectrum to extract different modes of the signal. The main steps of EWT are given as follows:

(1) Perform the Fourier transform on the signal, and set the Fourier spectrum normalization in the range of $[0,2\pi]$, according to the aroma criterion, only the signal on $[0,\pi]$ is considered in the subsequent analysis.

(2) The support of Fourier is divided into N regions, as shown in Figure 1, representing the boundary points in each region, the frequency band of each section is expressed as $\Lambda_n = [\omega_{n-1}, \omega_n]$, and the width of the transition region is expressed as $T_n = 2\tau_n$. The empirical scale function and the empirical wavelet function are shown in the following equation.

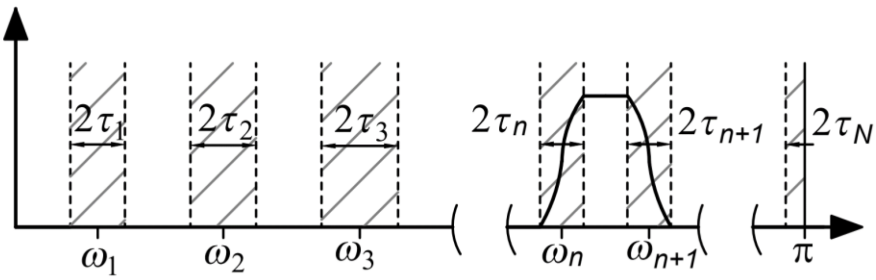

Figure 1. The EWT spectrum segmentation

$$\varphi_n \begin{cases} 1, \left(|\omega| \le (1-\gamma)\omega_n\right) \\ \cos\left\{\frac{\pi}{2}\beta\left[\frac{1}{2\gamma\omega_n}\left(|\omega|-(1-\gamma)\omega_n\right)\right]\right\}, \\ \left((1-\gamma)\omega_n\right) \le |\omega| \le (1+\gamma)\omega_n \\ 0, (\text{other}) \end{cases} \tag{1}$$

$$\psi_n \begin{cases} 1, (1+\gamma)\omega_n \le |\omega| \le (1-\gamma)\omega_{n+1} \\ \cos\left[\frac{\pi}{2}\beta\left(\frac{1}{2\gamma\omega_{n+1}}\left(|\omega|-(1-\gamma)\omega_{n+1}\right)\right)\right], \\ (1-\gamma)\omega_{n+1} \le |\omega| \le (1-\gamma)\omega_{n+1} \\ \sin\left[\frac{\pi}{2}\beta\left(\frac{1}{2\gamma\omega_n}\left(|\omega|-(1-\gamma)\omega_n\right)\right)\right], \\ (1-\gamma)\omega_n \le |\omega| \le (1-\gamma)\omega_n \\ 0, (\text{other}) \end{cases} \tag{2}$$

where $\beta(x)=x^4\left(35-84x-70x^2-20x^3\right)$ $\tau_n=\gamma\omega_n, 0<\gamma<1$， $\gamma<min_n\frac{\omega_{n+1}-\omega_n}{\omega_{n+1}+\omega_n}$

Detail factor $W_f^{\varepsilon}(n,t)$ and approximation coefficients $W_f^{\varepsilon}(0,t)$ are respectively shown in Equation (3) and (4):

$$W_f^{\varepsilon}(n,t)=\langle f,\psi_n\rangle=F^{-1}\left[f(\omega)\overline{\psi}_n(\omega)\right] \tag{3}$$

$$W_f^{\varepsilon}(n,t)=\langle f,\psi_n\rangle=F^{-1}\left[f(\omega)\overline{\varphi}_n(\omega)\right] \tag{4}$$

Where <, > means the inner product. The superscript refers to the conjugate of variables. $\bar{\varphi}$ means $\wedge$and $F^{-1}[\cdot]$ represent the variables in the form after the Fourier transformation and the inverse Fourier transformation, respectively.

The reconstructed signal $f(t)$ is defined as:

$$f(t)=F^{-1}\left[W_f^{\varepsilon}(0,\omega)\varphi_1(\omega)+\sum_{n=1}^{N}W_f^{\varepsilon}(n,\omega)\psi_n(\omega)\right] \tag{5}$$

Therefore, the eigenmode component $f_i(t)$ obtained by EWT is defined as:

$$f_i(t)=W_f^{\varepsilon}(i,t)*\psi_k(t) \tag{6}$$

3. Component screening principles

Each component of the decomposed MRA has more or less shock signals, so it needs to be filtered according to the index. The correlation coefficient indicates the correlation between the MRA component and the original signal, but it is easily disturbed by noise. The magnitude of the steepness value is related to the distribution density of the signal, but if the component amplitude is large, it is easy to be ignored. The literature[9] calculates the absolute value of the correlation coefficient and the normalized steepness value for each MRA, respectively define R as the parameter for the sum of the correlation coefficient and the steepness coefficient of MRA:

$$R=\frac{K_c}{K_0}+r_c \tag{7}$$

where K_c is the steepness value of each component, K_0 is the original signal steepness value, and r_c is the absolute value of the correlation coefficient for each component. To calculate the original signal steepness value and threshold K_0 and T, the threshold calculation formula of the correlation coefficient method is given as:

$$T=\sqrt{\frac{\sum_{i=1}^{n}\left(r_c-\overline{r_c}\right)^2}{n}} \tag{8}$$

Define the contrast parameter D, which has the following formula:

$$D=1+T \tag{9}$$

The use of this screening principle to screen each MRA component decomposed by EWT can effectively avoid the one-sidedness of a single criterion and retain more effective information for subsequent feature extraction. After many simulations with different EWT adaptive decomposition layers, the optimal number of decomposition layers is determined to be nine layers, which can take into account the fault signal of the rolling element of the inner ring and outer ring at the same time, making it filterable.

4. MED principle

MED is a technique commonly used in rotating machinery vibration to detect bearing faults, aiming to extract large sharp pulses in the signal, attenuate the effects of noise in the frequency band, and enhance the characteristic composition of the pulse signal. Wiggins et al. first proposed the minimum entropy solution convolution and proposed it as an iterative FIR filter selection problem [10]. Suppose the vibration signal $y(n)$ can be expressed as follows:

$$y(n) = h(n) \bullet x(n) + e(n) \tag{10}$$

where $h(n)$ is the transfer function; $x(n)$ is the fault signal; $e(n)$ is the noise signal.

The fault signal $x(n)$ gradually loses the impact characteristics of the original signal after passing through the environment and transmitting the attenuation response $y(n)$, and the information in the source signal becomes chaotic, that is, the entropy value increases the process. The purpose of MED is to eliminate the convolution effect by finding an optimal inverse filter $w(n)$, and obtain an inverse convolution signal $I(n)$ similar to the fault signal $x(n)$, that is:

$$I(n) = y(n) \bullet w(n) = \sum_{i=1}^{L} w(n) y(n-i) \tag{11}$$

$$\frac{\partial I(n)}{\partial w(i)} = y(n-i) \tag{12}$$

where L is the order of the inverse filter $w(n)$.

Wiggins measures the magnitude of the entropy of the signal $I(n)$ by calculating its norm and uses it as an objective function to obtain the optimal output.

$$O_2^4(w(i)) = \sum_{i=1}^{n} I^4(i) \Big/ \left[\sum_{i=1}^{n} I^2(i) \right]^2 \tag{13}$$

To make the norm of equation (11) maximum, let it be derived:

$$\frac{\partial O_2^4(w(n))}{\partial w(n)} = 0 \tag{14}$$

The combined equation (11) yields:

$$\sum_{n=1}^{N} I(n)^3 y(n-i) \Big/ O_2^4(w(i)) = \sum_{p=1}^{L} w(p) \sum_{n=1}^{N} y(n-i) y(n-p) \tag{15}$$

The matrix form is expressed as:

$$C = WA \tag{16}$$

$$W = CA^{-1} \tag{17}$$

where W is the coefficient matrix of the inverse filter; C is the cross-correlation matrix between the output signal and the input signal; A is the input signal autocorrelation matrix.

5. Experimental verification

To verify the effectiveness of the proposed method in the actual rolling bearing fault diagnosis, the bearing fault data of the Bearing Center of Western Reserve University in the United States was used as the analysis object for fault diagnosis, and the experimental platform was composed of a motor with a power of 1.5kw, a torque sensor/decoder, a power tester and an electronic controller. The bearing type is 6205-2RS JEM SKF deep groove ball bearings with 9 rolling elements. The specific bearing data is shown in Table 1.

Table 1. 6203-2RS JEM SKF deep groove ball bearings

Contact angle /°	Section diameter /mm	Ball diameter /mm	Outside diameter /mm	Inner diameter /mm	Number of rolling bodies
0	28.50	7.94	52	25	8

The experimental sampling frequency is fs=12kHz, the motor speed is 1772r/min, and the corresponding conversion frequency is f_r=29.53Hz. According to the bearing parameters and

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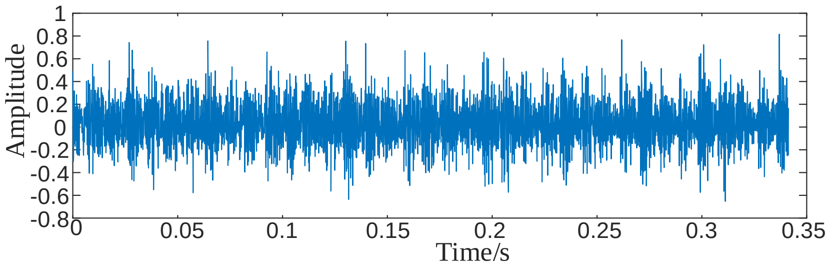
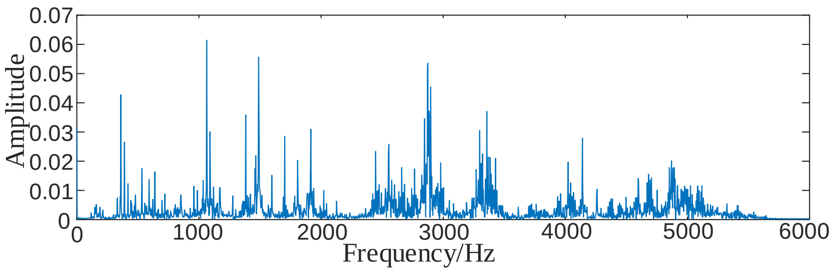
frequency, the fault frequency f_i=159.93Hz and the outer ring failure frequency f_o=105.87Hz can be calculated. In this paper, the filter order size[11] uses filtersize=100.

5.1. Outer ring signal

The time domain diagram and frequency domain diagram of the original signal of the bearing outer ring are shown in Figure 2, and it can be seen that the original signal contains a large amount of random noise and cannot accurately extract the characteristic frequency of the fault.



(a) Time domain waveform



(b) Frequency domain waveform

Figure 2. The characteristics of outer ring signal

In order to remove the random noise, accurately extract the fault characteristic frequency, we use EWT to decompose the original signal, and the specific decomposition is shown in Figure 3. We calculate the number of correlations and steepness values of each component, and use the relevant steepness filtering criterion to calculate the values and values, and select components greater than D for reconstruction.

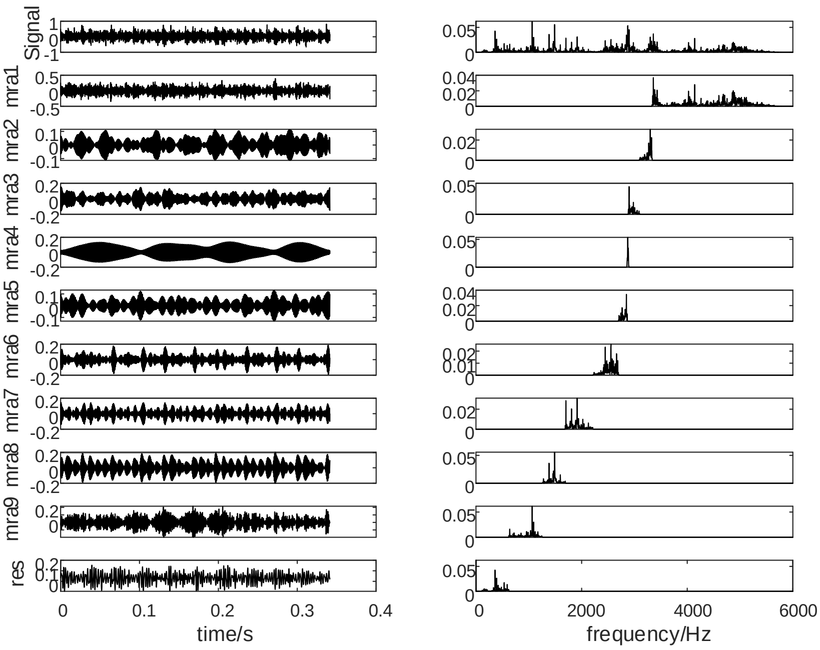


Figure 3. The schematic diagram of each component after the EWT decomposes the outer ring signal

The autocorrelation coefficient and steepness values for each MRA component are calculated as shown in Table 2 below.

Table 2. The specific parameters of MRAs

	MRA1	MRA2	MRA3	MRA4	MRA5	MRA6	MRA7	MRA8	MRA9
Correlation Coefficient	0.50	0.22	0.30	0.39	0.24	0.27	0.25	0.36	0.34
Kurtosis	3.29	2.67	2.61	2.06	2.67	3.88	3.21	2.82	2.76
R	1.50	1.04	1.09	1.01	1.05	1.44	1.23	1.22	1.21

According to (7)~(9), D is calculated as 1.08. As can be seen from Table 2, MRA 2, MRA 4, and MRA 5 have larger R values than D and contain more useful signals, which need to be reconstructed and denoised. The reconstruction signal is shown in Figure 4, the superimposed signal is used for MED denoise, and the time domain plot of the denoising signal is shown in Figure 5.

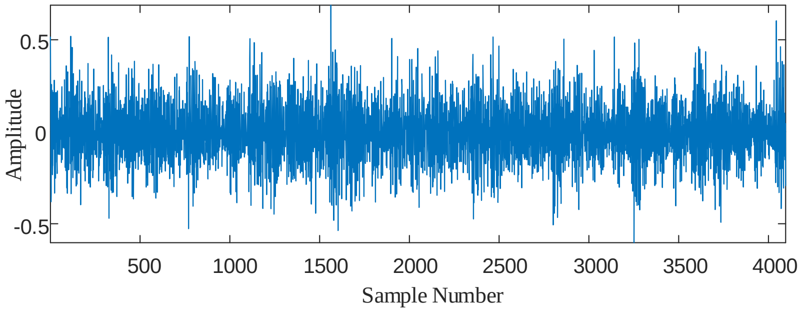


Figure 4. The inner outer signal after screening

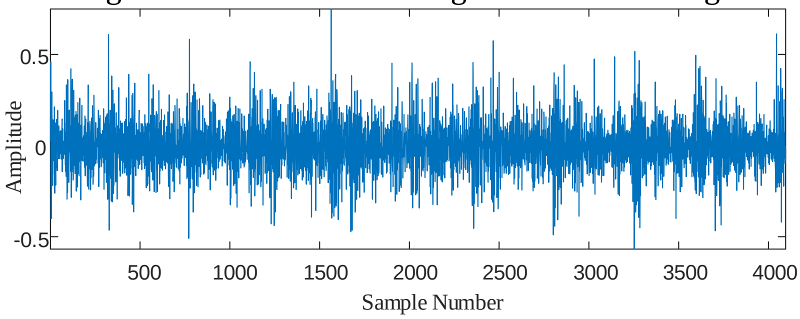


Figure 5. The signal after MED noise reduction

The denoised signal is superimposed with other MRA components after EWT decomposition, and finally the envelope spectrum analysis is carried out, and the envelope spectrum of the reconstructed signal is shown in Figure 6. The conversion frequency and fault frequency are clearly visible, and the relative error of the fault frequency is 0.38%. As a result, the fault features can be accurately extracted.

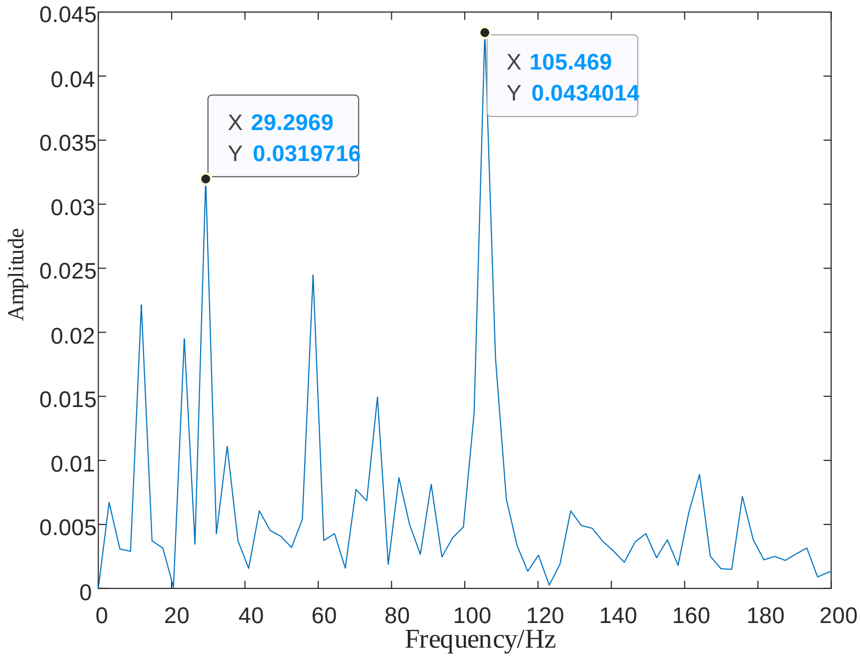
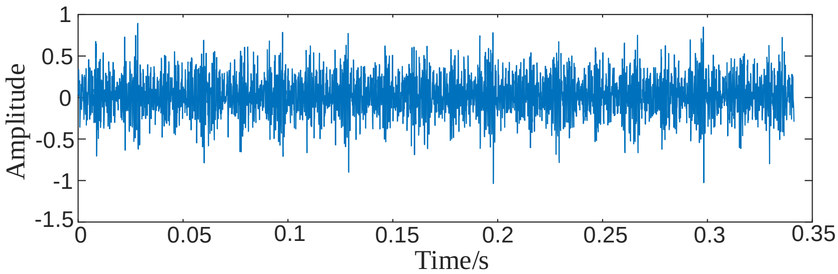


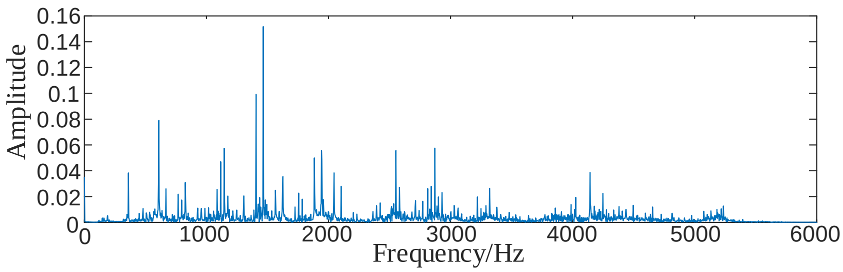
Figure 6. The envelope spectrum of reconstructed signal

5.2. Inner ring signal

The time domain diagram and frequency domain diagram of the original signal of the inner ring are shown in Figure 7. The outer circle signal contains noise frequency influence, and we cannot accurately determine the fault characteristics and require subsequent noise reduction processing.



(a) Time domain waveform



(b) Frequency domain waveform

Figure 7. The characteristics of inner ring signal

The signal is decomposed by EWT to obtain Figure 8, and the components are screened with the relevant steepness criterion to reconstruct the signal that needs to be denoised, and then we obtain Figure 9.

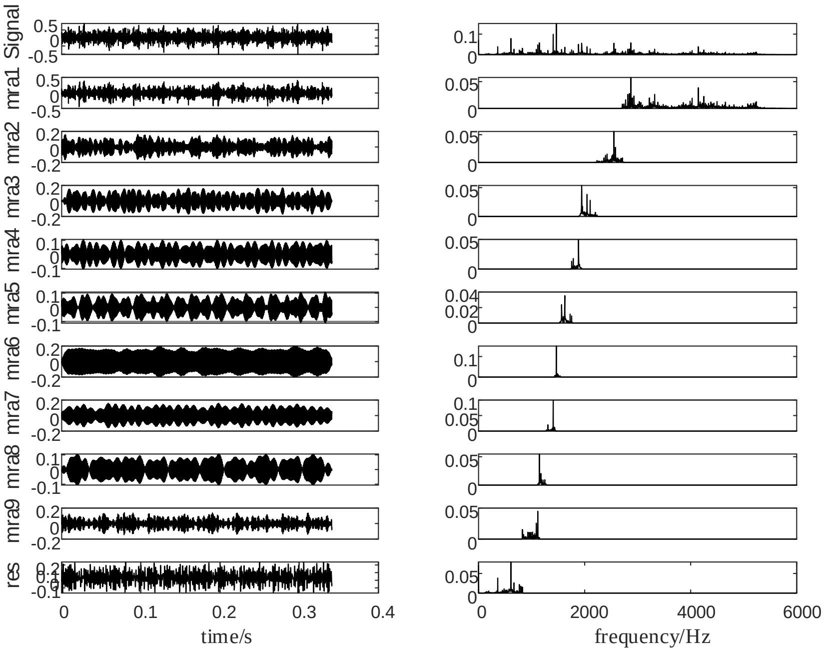


Figure 8. The schematic diagram of each component after the EWT decomposes the inner ring signal

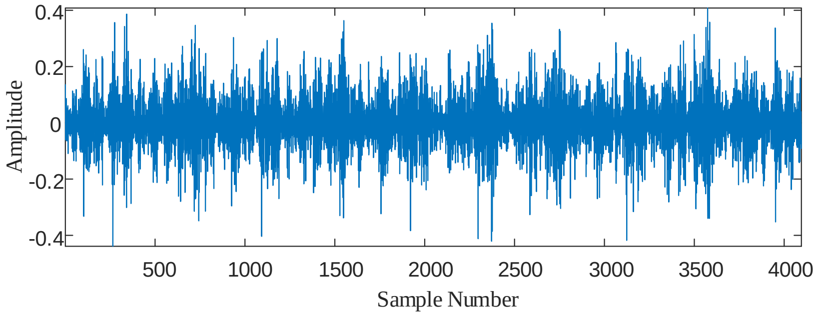


Figure 9. The inner ring signal after screening

The reconstructed signal is denoised by MED, the filter size is set to 100, and the time domain diagram of the signal obtained after denoise is shown in Figure 10. Then we superimpose it with the low-noise MRAs and finally analyze the envelope spectrum to obtain the envelope spectrum shown in Figure 11. It can be seen that the conversion frequency and failure frequency are 1 time and 2 times, and the relative error of the fault frequency is 1.08%. So the fault characteristics can be accurately extracted.

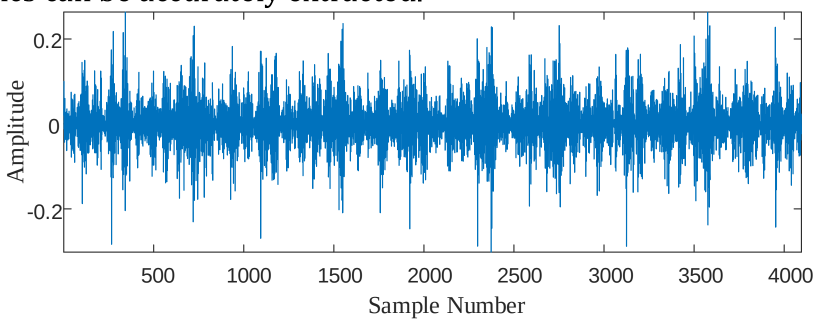


Figure 10. The signal after MED denoise

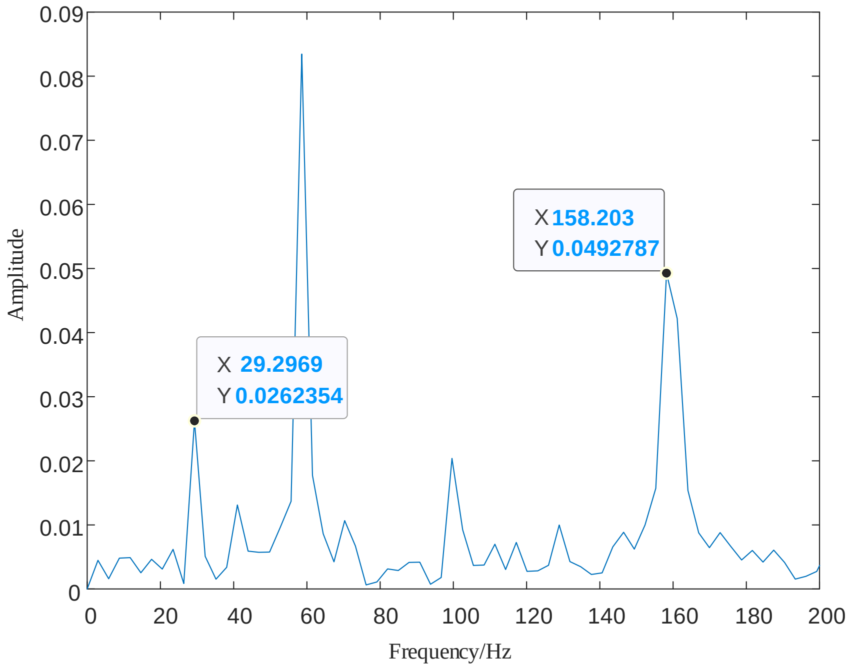


Figure 11. The envelope spectrum of reconstructed signal

6. Conclusion

In this paper, a new method for bearing fault diagnosis is proposed, which first uses adaptive EWT to decompose the original signal to obtain nine MRAs, and then combines the steepness value and autocorrelation coefficient for component screening, retains the low noise component, reconstructs the high noise component, and then performs MED noise reduction on the reconstructed signal. Finally, the noise reduction signal is superimposed with the MRA component with low noise content and the envelope spectrum analysis is carried out, and the method can effectively extract the fault characteristics and reduce noise interference by analyzing the measured fault signal.

In order to accurately extract the bearing fault characteristics under the background of noise, the results show that a rolling bearing fault feature extraction method based on EWT and MED is verified by experimental measured signals. The specific conclusions of the paper are given as follows:

(1) EWT is very adaptive and preserves the structure and detail of the signal well.

(2) According to the relevant steepness screening criteria, only the MRA components with high noise content are denoised, which can effectively retain useful information.

(3) The MED noise reduction method has a stable effect, and it can be considered that setting the appropriate number of filter layers can better improve the fault characteristics.

Acknowledgements

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References

[1] Z.C. Xu, L.J. Wang, J.W. Liu, W.C. Huang, B.J. Chen, Bearing fault feature extraction method based on multi-layer noise reduction, Machine Tool & Hydraulics 49 (16) 2021 174-179.

[2] Y. Liu, L.J. Wang, L.J. Li, B.J. Chen, Z.C. Xu, K.L. Cai, Bearing fault analysis based on SVD-CEEMDAN and KLD, Machine Tool & Hydraulics 50 (17) 2022 195-199.

[3] J. Antoni, G. Xin, N. Hamzaoui, Fast computation of the spectral correlation, Mechanical Systems and Signal Processing 92 (2017) 248–277.

[4] J. J. Sheng, G. Chen, Y. X. Kang, et al. An improved EWT method for fault diagnosis of rolling bearings, Journal of Aerospace Power (2023-1-15) 1-13 .

[5] W. Li, Fault Diagnosis Method for EMU Traction Motor Bearings Based on Minimum Entropy Deconvolution, Bearing Journal 505 (12) 2021 56-60.

[6] H. Endo, R.B. Randall, Application of a minimum entropy deconvolution filter to enhance autoregressive model based gear tooth fault detection technique, Mechanical Systems and Signal Processing 21 (2) 2007 906-919.

[7] Z.C. Xu, L. J. Wang, J. W. Liu, W. C. Huang, B. J. Chen, The Method of Bearing Fault Information Analysis Based on Kurtosis Criterion, J of China Three Gorges Univ. (Natural Sciences) 43 (06) 2021 100-105.

[8] J. Gilles. Empirical Wavelet Transform, IEEE Transaction on Signal Processing 61 (16) 2013 3999-4010.

[9] X.C. Luan, Y.Z. Li, S. Xu, et al. Rolling bearing fault diagnosis method based on wavelet packet transform and CEEMDAN, Journal of Aerospace Power (2022-12-12) 1-16.

[10] R.A. Wiggins, Minimum entropy deconvolution, Geoex ploration 16 (1/2) 1978 21-35.