Rolling bearing fault diagnosis method based on OSFFDM and adaptive multi-scale weighted morphological filtering

Siqi Huang1*, Xinglong Wang2, Siguo Yang1, and Zhiyin Tan1

1School of Electrical Engineering, Chuzhou Polytechnic, Chuzhou, Anhui, 23900, China
2School of Mechanical Engineering and Automation, Fuzhou University, Fuzhou, Fujian, 350116, China
*Corresponding author’s e-mail: huangsiqi@chzc.edu.cn

Abstract: The Order-statistic filtering Fourier decomposition (OSFFDM) is a decomposition method that obtains components of different frequency bands by pre-processing the Fourier spectrum. The OSFFDM method overcomes the problem of a large number of invalid components in FDM. However, OSFFDM only considers the frequency band search problem, and does not really solve the interference problem of noise and irrelevant components. To solve this problem, a bearing fault diagnosis method named OSFFDM and adaptive multi-scale weighted morphological filtering (AMWMF) is proposed. First, the order-statistic filtering and smoothing methods are used to fit the envelope trend term of the Fourier frequency spectrum of the raw signal. Second, according to the envelope trend, a series of single components are obtained through the idea of segmentation and reconstruction. Then, the AMWMF is used to filter the component with the maximum kurtosis value. Finally, the envelope spectrum is used to analyze the filtered signal. In the analysis of the actual collected bearing vibration signal, the diagnostic results of the combination of OSFFDM and AMWMF and existing methods such as EMD and FDM are studied and compared. From the comparison results, it can be observed that the OSFFDM and AMWMF method can effectively identify bearing fault information. By calculating the signal-to-noise ratio (SNR) of the optimal component, the proposed method has a higher SNR, that is, less noise interference. The comparison of the diagnosis results further verifies the effectiveness and superiority of the OSFFDM and AMWMF method.

1. Introduction
The vibration signal, as an intuitive object containing fault information, is a very useful material for fault diagnosis of rotating machinery. Due to the diversity and complexity of mechanical system and the coupling phenomenon of forces between parts, vibration signal is often non-stationary. As a result, traditional analysis methods for stationary and linear vibration signals are no longer suitable for processing such non-stationary vibration signals [1].

In the history of processing non-stationary signals, the empirical mode decomposition (EMD) method was first introduced by Huang in 1998 [2]. The EMD is a type of data-driven method and does not require pre-selection of basis functions. For a given non-stationary signal, it can be adaptively decomposed into a series of Intrinsic Mode Functions (IMF) and a remainder by EMD. Based on this, the EMD method has been widely and effectively used in various disciplines [3-5]. For example, Liu et al. applied EMD and Hilbert to the analysis of the vibration signal of the gearbox with a partial failure. Compared with the commonly used continuous wavelet transform, the detection of this method is more
effective [6]. Yang et al. applied EMD energy entropy to artificial neural network, and the obtained recognition rate demonstrate that the neural network method using EMD energy entropy as a feature can identify failure modes more accurately [7].

Subsequently, to improve the robustness of the fault information extraction ability, the signal decomposition method based on the time domain was converted to the frequency domain. For example, Gilles proposed empirical wavelet transform (EWT) [8]. The EWT uses adaptive frequency band division idea to decompose the raw frequency domain signal into multiple amplitude-modulation and frequency-modulation modes. The envelope method supported by the order-statistical filter (OSF) was used by Hu to improve the segmentation effect of EWT, and the effective effect of the new method was proved in simulated and measured signals. However, the choice of window length in this method takes a lot of time to debug [9]. Then, the variational Modal Decomposition (VMD) is developed to decompose the raw signal into a given number of components by by finding the optimal solution of the model [10]. However, the penalty factor and the number of modes in the VMD method need to be set in advance based on expert experience, and the selection of different parameters has a great impact on the final decomposition result.

Recently, a new method known as Fourier decomposition method (FDM) is proposed by Singh [11]. Different from existing decomposition methods, the FDM has the characteristics of orthogonality, completeness and locality. Under the action of this method, the original signal was decomposed into a series of single components of different frequency bands. And the FDM method can extend the traditional Fourier representation method of constant amplitude and constant frequency to the generalized Fourier representation of time-varying amplitude and time-varying frequency. Once FDM was proposed, it was applied to the research in medicine and machinery, and achieved promising results. [12-15]. However, for the actually collected rolling bearing signal, due to the complexity of the Fourier frequency spectrum of the original signal, the boundary obtained by the FDM method directly dividing the original spectrum is unreasonable, resulting in more invalid components.

In view of the shortcomings of FDM, OSFFDM was recently proposed [16]. This method obtains components of different frequency bands by pre-processing the spectrum, which can effectively avoid the shortcoming of some invalid components generated by FDM. Unfortunately, the OSFFDM only solves the problem of component search, it does not achieve the purpose of denoising. Therefore, to overcome this shortcoming, a fault diagnosis method combining OSFFDM and adaptive multi-scale weighted morphological filtering (AMWMF) is proposed. The proposed diagnosis method is roughly divided into three steps: First, the OSF is applied to pre-process the original frequency spectrum of the signal. The purpose of this step is to simplify the spectrum and facilitate segmentation. Second, based on the OSF spectrum, the Fourier intrinsic modes functions are searched according to the search method from the left to the right of the frequency spectrum. Next, among the obtained components, the component with the largest kurtosis value is chosen as the most suitable mode. Then, to solve the interference of irrelevant components and a lot of noise in the frequency band, the AMWMF is used to deal with the optimal mode. Finally, the envelope spectrum is applied to extract fault information of the AMWMF filtered result. The OSFFDM and AMWMF method is used to the actual measurement signal analysis. It can be observed from the diagnosis results that the proposed method can extract the optimal frequency band components and perform denoising, which is superior to the compared EMD and FDM methods.

2. Order-statistic filtering Fourier decomposition
The non-stationary vibration signal can be decomposed by the OSFFDM method into the sum of multiple single components called the Fourier Intrinsic Mode Function (FIMF), where the instantaneous frequency of each component has a physical meaning. However, generally, the Fourier frequency spectrum of the mechanical vibration signal is accompanied by more noise and is usually more complicated. And the OSFFDM is difficult to directly solve this problem effectively. Therefore, proper pre-processing of the Fourier spectrum is required. In the OSFFDM method, the original frequency
spectrum is simplified through OSF and smoothing, so that the result of the segmentation is more reasonable.

2.1. Order-statistic filtering

OSF is to determine the width of the window after obtaining the extreme point situation, and then envelope the signal to achieve filtering of the data in the window. The advantage of OSF processing signal is that it can effectively reduce irrelevant frequency components and retain the main frequency components with larger peaks in the spectrum. The calculation steps of OSF are as follows [17]:

1. Search for peaks in the frequency spectrum and count the number.
2. Calculate the distance between two adjacent maximum peak points obtained by step (1), and define the minimum distance value as the initial window width of OSF.
3. Constantly change the size of the OSF window, and select the window size where the maximum component of the kurtosis value is located as the most suitable window width.

There are three filtering methods for OSF, which are filtering with the help of the maximum, minimum and median values. Take the maximum value filter as an example to illustrate.

For a signal $Y_i(f), i \in (1, L)$ with a length of $L$, the result output by the OSF is denoted as $Evp_{osf}(f)$.

The window width $W_{osf}$ divides the Fourier spectrum of the raw signal $Y_i(f)$ into $L - W_{osf} + 1$ parts, and the $j$-th interval is $[Y_j(f), Y_{j+1}(f), Y_{j+2}(f), \ldots, Y_{j+W_{osf}-1}(f)], 1 \leq j \leq L - W_{osf} + 1$. Therefore, the upper envelope filtered by OSF can be expressed by the following formula:

$$
Evp_{osf}(f) = \max\{\sum_{j=1}^{L-W_{osf}+1} \{Y_j(f), Y_{j+1}(f), Y_{j+2}(f), \ldots, Y_{j+W_{osf}-1}(f)\}\}
$$

(1)

The length of the original data will be reduced after OSF envelope processing. Among them, in front of the leftmost window and behind the rightmost window, there will be two data points lost during the envelope. However, the lost data can be supplemented by mirror continuation.

A data sequence [3,4,2,5,7,5,1,2,7,10,6,2,3,5,4,2] is used to illustrate the operating procedures of the OSF algorithm. The detailed envelope steps are discussed as follows: First, count the number of peaks in the raw data sequence and calculate the distance between adjacent maximum points. The local maximums in the given sequence are 4, 7, 10, and 5. By calculating the distance between each other, we can find that the minimum distance between these peaks is 3. So the window width is set to $W_{osf} = 3$.

Then, add the data points $(W_{osf} - 1)/2 = (3 - 1)/2 = 1$ at the leftmost and rightmost of the original data sequence through the mirror continuation method, that is, add data 4 to the leftmost and rightmost sides of the original sequence to obtain a new data sequence. Finally, the window with a window width of 3 is used to filter the data from left to right, and the peaks in each window is taken to produce the filtered result described in the Figure 1. The OSF can retain the main frequency components with larger amplitudes that facilitating the division of the frequency spectrum.

When using OSF to get the upper envelope of the measured signal, the average value of the distance between adjacent peaks can be estimated with the following formula:

$$
d_{osf} = \frac{L}{n}
$$

(2)

where, $n$ is the total number of peaks in the Fourier spectrum, and $L$ is the data length. Therefore, the size of the first window defaults to the odd number closest to $d_{osf}$, and the window size is continuously adjusted in each cycle, that is, $W_{next} = W_{osf} + 2$.

The Fourier spectrum is only pre-processed by the OSF method, which is far from enough for diagnosing bearing faults. Wherefore, it is indispensable to segment the pre-processed spectrum and select components containing abundant fault information for accurate diagnosis. The segmentation method used in the OSFFDM method is to use the minimum point between adjacent peaks as the split boundary to reasonably segment the processed spectrum.
2.2. The algorithm flow of OSFFDM

The specific implementation procedures of the OSFFDM method are as follows:

1. The original vibration signal $x(t)$ is subjected to FFT to get the Fourier spectrum $F(f)$.

2. Pre-process spectrum $F(f)$. The OSF is used to carry out envelope filtering processing on Fourier spectrum $F(f)$. The window size is uninterrupted changed, and the window of the component with the largest kurtosis value is selected as the most suitable window width.

3. The upper envelope after OSF processing is smoothed. In the OSFFDM method, the moving average method is applied, and finally the processed spectrum $Y(f)$ is obtained.

4. The minimum point between the adjacent peaks is used as the split boundary to segment the processed spectrum $Y(f)$. Then the boundary set $B_k$ is obtained.

5. The FIMF components of each interval in the boundary set $B_k$ are obtained by inverse FFT.

The flowchart of the OSFFDM method is described in Figure 2.

3. Adaptive multi-scale weighted morphological filtering

Since there are still many noise components in the envelope spectrum of the components decomposed by OSFFDM, it is necessary to eliminate the background noise and highlight the fault characteristics. AMWMF is a noise reduction method that can effectively suppress positive and negative impulse noises. It can overcome the shortcomings of morphological filtering that it needs to rely on prior knowledge when selecting structural elements and scale intervals, and is susceptible to interference by human factors. The filtering principle of this method is as follows:

First, find the position of the extreme point. For a given vibration signal, search for the location corresponding to its maximum point and minimum point. Then, determine the parameters of structural elements. Finally, filter results of different scales are obtained according to the raw signal and the structural elements determined in the previous two steps.

4. Measured signal analysis

To verify the effective effect of the OSFFDM and AMWMF method, the measured signal is used for diagnostic analysis. The construction of the test bench and the layout of the sensors are described in Figure 3. In the experiment, the vibration signal generated by the SKF 6206-2RS1 rolling bearing with with a cutting depth of 0.4 mm on the inner ring (Figure 4) was collected. The sampling frequency is 8192 Hz, the load is 5 KN, and the motor rotation speed is 900 r/min. The waveform diagram and frequency spectrum of the measured signal are revealed in Figure 5 and Figure 6, respectively. The fault characteristic frequency $f_i=80$ Hz is obtained by theoretical calculation.
First, the proposed fault diagnosis method is applied to extract the fault information of the measured data. By constantly changing the window width, the optimal window width is obtained as $W_{\text{opt}}=97$, and the maximum peaks in each window is taken from left to right to form the filtered result as shown in Figure 7. Since there are many identical extreme points in the result of OSF processing, which is not conducive to segmentation. So those extreme points need to be smoothed, and the smoothing result is shown in Figure 8. Second, by finding the extreme points in the smoothing result and performing spectrum segmentation, the boundary is obtained and describe by the dashed line in Figure 8. Then, the IFFT is performed on the signals within the adjacent boundaries to obtain several components. Finally, the component with the largest kurtosis value is chosen for AMWMF filtering, and the envelope spectrum of the filtered result is described in Figure 9(a). It can be found that the fault frequency $f_i$ and its multiplication $(2~6)f_i$ is prominent, which is in line with the failure characteristics of rolling bearings.
Then, for comparison, EMD and FDM are applied to decompose the above-mentioned bearing vibration signals. In the decomposition results of EMD and FDM, the component with the maximum kurtosis is chosen for envelope spectrum analysis. The envelope spectrum obtained by EMD is shown in Figure 9(b). We can see the obvious rotation frequency \( f_r \) and fault characteristic frequency (FCF) \( f_i \), but the multiplier of the \( f_i \) is submerged by background noise, which is not conducive to effective diagnosis. Figure 9(c) illustrates the envelope spectrum of the optimal component obtained by FDM. In Figure 9(c), only the FCF can be seen, and the high frequency part has almost no information. It can be found that the frequency interval of the component is narrower and contains less fault information.

Finally, to further discuss the effective effect and superiority of the OSFFDM and AMWMF method, the formula (3) [18] is used to calculate the SNR of the components obtained by the method of combining OSFFDM and AMWMF, EMD and FDM, and the results are described in Figure 10. From Figure 10, we can know that when the FCF is set at different multiples \( n \), the proposed methods all have the highest SNR, which is more effective than the compared EMD and FDM methods.

\[
\text{SNR} = 10 \log_{10} \left( \frac{p_{\text{signal}}}{p_{\text{noise}}} \right) = 10 \log_{10} \left( \frac{\sum_{i=1}^{NFFT} |p[i \times \text{round}(f_s / \Delta f) + 1]|}{\sum_{m=1}^{MUF} \sum_{n=1}^{NFFT} |p[i - n] + \sum_{m=1}^{MUF} |p[i \times \text{round}(f_s / \Delta f) + 1]|} \right)
\]

Where, NFFT is the length of the signal, \( f_s \) is the FCF, \( P[*] \) is applied to calculate the power of the raw signal, and \( \Delta f = f_s / L \).

Figure 10. The SNR results of the three methods

5. Conclusions
A fault diagnosis method for rolling bearings based on OSFFDM and AMWMF is proposed in this article. The obtained main conclusions are the following two:

1. The OSFFDM method uses an envelope method and smoothing processing, which can effectively optimize the Fourier spectrum and obtain a reasonable segmentation boundary.
2. The bearing fault diagnosis method combined with OSFFDM and AMWMF can effectively identify bearing faults, and the obtained components have a higher SNR, and are better than the compared EMD and FDM methods.

Acknowledgments
The work was supported by the University Natural Science Key Research Project of Anhui Province of China (No. KJ2019A1130) and the Professional Leader Project of Chuzhou polytechnic (No. ZD2019013). Thanks to Dr. Wang Xinglong for his guidance on this paper.

References
[1] Wang X.L., Zheng J.D., Pan H.Y., et al. (2020) Maximum envelope-based Autogram and Symplectic geometry mode decomposition based gear fault diagnosis method. Measurement, 174: 108575.
[2] Huang N.E., Shen Z., Long S.R. (1998) The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. Proceedings Mathematical & Engineering Sciences, 454: 903-995.

[3] Park S., Kim S., Choi J. (2018) Gear fault diagnosis using transmission error and ensemble empirical mode decomposition. Mechanical Systems and Signal Processing, 108: 262-275.

[4] Yu D. J., Cheng J.S., Yang Y. (2005) Application of EMD method and Hilbert spectrum to the fault diagnosis of roller bearings. Mechanical Systems and Signal Processing, 19: 259-270.

[5] Lei Y.G., Lin J., He Z.J. (2013) A review on empirical mode decomposition in fault diagnosis of rotating machinery. Mechanical Systems and Signal Processing, 35:108-126.

[6] Liu B, Riemenschneider S, Xu Y. (2006) Gearbox fault diagnosis using empirical mode decomposition and Hilbert spectrum[J]. Mechanical Systems and Signal Processing, 20: 718-734.

[7] Yang Y., Yu D.J., Cheng J.S. (2006) A roller bearing fault diagnosis method based on EMD energy entropy and ANN[J]. Journal of Sound & Vibration, 294: 269-277.

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

[9] Hu Y., Li, F.C., Li H.G. (2017) An enhanced empirical wavelet transform for noisy and non-stationary signal processing[J]. Digital signal processing, 60: 220-229.

[10] Dragomiretskiy K., Zosso D. (2014) Variational Mode Decomposition[J]. IEEE Transactions on signal processing, 62: 531-544.

[11] Singh P., Joshi S.D., Patney R.K. (2017) The Fourier decomposition method for nonlinear and non-stationary time series analysis. Proceedings of the Royal Society A: Mathematical, Physical and Engineering Science, 473: 20160871.

[12] Singhal A., Singh P., Fatimah B. (2020) An efficient removal of power-line interference and baseline wander from ECG signals by employing Fourier decomposition technique. Biomedical Signal Processing and Control, 57(SI).

[13] Elbi M.D., Kizilkaya A. (2017) Optimal Signal Reconstruction Based on the Fourier Decomposition Method. In: 10th International Conference on Electrical and Electronics Engineering (ELECO), Bursa, Turkey.

[14] Elbi M.D, Kizilkaya A. (2020) Multicomponent signal analysis: Interwoven Fourier decomposition method. Digital Signal Processing, 104: 1-25.

[15] Binish F., Pushpendra S., Amit S., Ram B.P. (2020) Detection of apnea events from ECG segments using Fourier Decomposition Method. Biomedical Signal Processing and Control,61: 1-10.

[16] Huang, S.Q., Zheng, J.D., Pan, H.Y., Tong, J.Y. (2021). Order-statistic filtering fourier decomposition and its application to rolling bearing fault diagnosis. Journal of Vibration and Control, 11: 107754632199759.

[17] Xu Y.G., Zhang K., Ma C.Y. (2019) Adaptive Kurtogram and its applications in rolling bearing fault diagnosis[J]. Mechanical Systems and Signal Processing, 130: 87-107.

[18] Li, J.P. (2018) Research on Fault feature extraction method of rotor Vibration signal. Lanzhou University of Technology, Gansu.