Research on EEMD for vibration extreme feature preserving of rotating machinery

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Abstract. Ensemble Empirical Mode Decomposition (EEMD) has been widely used due to the more advanced processing of mode mixing than Empirical Mode Decomposition (EMD). However, EEMD still suffers mode mixing in the vibration analysis of rotating machinery. It proposes Extremum Feature Preserving Ensemble Empirical Mode Decomposition (EFPEEMD) for the feature extraction of rotor systems in rotating machinery. In the method, a fluctuant variation (FV) index is developed to quantitatively recognize the amplitude of added noise on the basis of the empirical rules in EEMD. The results of a misalignment vibration signal of a rotor system and an inner race defect signal of a rolling bearing show that, the primary vibration modes can be extracted rapidly and independently based on the elimination of the non-stationary and non-linear interference. Moreover, the fluctuant variation index removes the originally manual and empirical steps, thus enhancing the accuracy and automation of EEMD on the basis of preserving the extreme information.

1. Introduction

The industrial rotating machinery have been widely used not only in the aerospace, national defense construction and other high-tech industries, but also in the petroleum chemical industry, metallurgy and other national pillar industry, such as steam turbine, generator and different types of compressors. The rotating equipment usually has a compact structure with big size and big weight, and long runs in a high speed and high-power way with strong vibration and noise interference. As the core part of rotary machinery, a rotor-bearing system is prone to be failure under vibration condition, which not only decreases its normal service life, but also reduces production efficiency. Therefore, it is significant to ensure the safety and stability of the production field and quickly and accurately identify the running state of rotating machinery, according to the vibration condition of the rotor-bearing system.

Correct analysis and effective extraction of the state parameters and dynamic response information of rotating machinery are the basis of subsequent fault pattern recognition [1]. However, vibration signals of rotating machinery often show significant harmonic frequency characteristics with non-linearity, non-stationarity and noise interference, which have been concerned for a long period [2,3]. Huang et al. proposed empirical mode decomposition [4], and initially established the time-frequency analysis system that measures the signal alternating with instantaneous frequency and expresses the signal components with basic mode components [5]. In this method, the application research in the field of mechanical equipment fault diagnosis was quickly obtained. Yu et al. [6] combined EMD and
envelope analysis for fault diagnosis of rolling bearings. Gai [7] used EMD to analyze the starting signal of the rotor and draw a Bode diagram. Liu et al. [8] used the B-spline curve EMD and Hilbert spectrum for gear box fault diagnosis. However, mode aliasing is easily caused by the abnormal events such as noise interference [9-12]. Wu et al. proposed ensemble empirical mode decomposition [13], which assists EMD with the white noise and effectively decrease the mode aliasing phenomenon. This method is also quickly applied in the field of fault diagnosis of rotating machinery. Cao et al. [14] studied the noise reduction of non-stationary signals during rotor start-up using EEMD. Yu et al. [15] studied the rotor local rubbing using EEMD and compared the effect with EMD. Lei et al. [16,17] used EEMD for rotor impact rub fault diagnosis and studied the noise adding method of EEMD. Chen et al. [18] studied the component selection of EEMD and the noise-adding times for noise reduction of rotor vibration signals. Zhang et al. [19] combined morphological filtering, EEMD, sample entropy and grey correlation analysis to study the classification of common rotor faults. Though the achievements in the above research on rotor vibration pattern extraction, EEMD is still disturbed by mode mixing with the nonlinearity, non-stationarity and noise interference, which affect the rapid and accurate fault identification. It lies in the problem of quantitative selection of noise amplitude parameter. Therefore, an indicator is needed to be constructed to quantitatively select the parameters of noise amplitude and further solve the mode aliasing of EEMD, which is expected to accurately extract fault features of rotating machinery.

In this study, the nonstationary information of the rotor-bearing transmission system of the rotating machinery was investigated. EEMD method was proposed with extreme feature preserving, which improves the application ability of traditional EEMD in vibration analysis of rotating machinery.

2. Ensemble empirical mode decomposition (EEMD)

2.1. Flow of the algorithm

EEMD uses the uniform statistical distribution of the white noise spectrum to provide a uniform distribution for the decomposition scale of the investigated signals. Furthermore, mode mixing is eliminated by average effect due to the zero-mean property of the white noise, which is equal to the average of EMDs. The steps of EEMD algorithm can be summarized as follows:

Step 1: The original signal \( x(t) \) plus the gaussian white noise \( n_i(t) \) whose mean value is 0 and whose amplitude and standard deviation are constant for \( N \) times, as shown in equation (1).

\[
x_i(t) = x(t) + n_i(t)
\]  

where, \( i = 1, 2, \ldots, N \).

Step 2: Performing EMD on each \( x_i(t) \), \( K_i \) IMFs and a residual \( r_i(t) \) are obtained, as shown in equation (2).

\[
x_i(t) = \sum_{j=1}^{K_i} C_{ij}(t) + r_i(t)
\]  

where, \( C_{ij}(t) \) denotes the \( j^{th} \) IMF with the \( i^{th} \) noise assisted signal, \( j = 1, 2, \ldots, K_i \).

Step 3: Carrying out the ensemble process on the obtained IMFs to suppress the effect of the added gaussian white noise for several times, the real IMF and a residual \( r(t) \) were obtained, as shown in equations (3) and (4).

\[
C_j(t) = \frac{1}{N} \sum_{i=1}^{N} C_{ij}(t)
\]  

\[
r(t) = \frac{1}{N} \sum_{i=1}^{N} r_i(t)
\]
where, $C_j(t)$ is the $j^{th}$ IMF of the decomposed original signal.

Step 4: Obtain the $K$ IMFs and a residual $r(t)$, as shown in equations (5).

$$x(t) = \sum_{j=1}^{K} C_j(t) + r(t)$$  \hspace{1cm} (5)

2.2. Noise amplitude selection

Reference [13] points out that the effect of white noise on the investigated signal follows the statistical rule as shown in equation (6).

$$\varepsilon_n = \frac{\varepsilon}{\sqrt{N}} \text{ or } \ln \varepsilon_n + \frac{\varepsilon}{2} \ln N = 0$$  \hspace{1cm} (6)

where, $\varepsilon_n$ is the deviation between the original signal and the reconstructed signal, $\varepsilon$ is the amplitude of white noise, and $N$ is the number of the added noise.

According to the formula (6), the signal decomposition precision is directly proportional to the noise amplitude level, and inversely proportional to the open square of the noise-adding number $N$. A small $\varepsilon$ is difficult to modify the local extreme point of the signal. A large $N$ will increase the complexity of the algorithm. Therefore, $\varepsilon$ is taken to be 0.2 times of the standard deviation of the investigated signal according to the noise adding experiment, as recommended in literature [16]. $\varepsilon$ can be smaller if the signal is mainly characterized by higher frequency. On the other hand, $\varepsilon$ can be higher if the signal is mainly characterized by lower frequency.

3. EFPEEMD for fault signal of rotating machinery

3.1. Vibration mode extraction

The goal of EEMD is to decompose the signal into IMFs and a residual with frequency ranging from high to low based on noise reduction. From the engineering experience of the rotor vibration analysis, IMFs with high frequency can be categorized to random noise, and the low frequency area of the IMFs may be classified as trends, false or residuals. If the invalid IMFs can be removed, the effective IMFs are obtained to describe the vibration mode of the rotating machinery. These IMFs can be analyzed separately, and also can be used for signal reconstruction. For the special conditions of the rotating machinery, the IMF component obtained by EEMD still has a certain degree of frequency aliasing. Therefore, the component selection is aimed at preserving the main vibration mode.

3.2. Parameters of EEMD

The typical vibration band of an investigated signal from the rotating machinery is mainly concentrated in the range of integer frequency within the base frequency, dividing frequency and octuple base frequency. It is generally classified as a lower frequency signal. Therefore, $\varepsilon$ can be set as 0.2 times of the standard deviation of the analysis signal. However, the qualitative process needs artificial assistance. It is necessary to ensure a small distortion between the reconstructed signal and the original signal when we need a high orthogonality between IMFs due to noise inducing the increase of the signal disorder degree and the change of extreme point. Therefore, a Fluctuant Variation indicator is developed to measure the extreme fluctuation between the original signal and reconstructed signal, and further quantitatively determine the noise amplitude parameters, as shown in the equation (7). If $FV$ has a small value, it is considered that the waveform distortion is small between the original signal and the reconstructed signal, and the corresponding noise amplitude parameter is optimal.

$$FV = \left| \frac{y_p - x_p}{y_{rms} - x_{rms}} \right|$$  \hspace{1cm} (7)
where, $x_p$ is the peak of the original signal, $x_{rms}$ is the mean square amplitude of the original signal, $y_p$ is the peak of reconstructed signal, and $y_{rms}$ is the mean square amplitude of the reconstructed signal.

Additionally, the number of added noise N can be set as 100 according to the literature [13]. In [18], N can be a small value on the base of the vibration property of the rotating machinery.

3.3. Parameters of EEMD
The overall process framework is shown in figure 1.

![Figure 1. FEPEEMD for fault signal of rotating machinery.](image)

Step 1: Set the initial noise amplitude of EEMD according to equation (6);
Step 2: Analyze the investigated signal by EEMD and obtain IMFs;
Step 3: Choose IMFs and reconstruct the signal;
Step 4: calculate the FV index and step to adjust the noise amplitude;
Step 5: Repeat Step1 to Step4 until satisfying the termination condition and output the optimal EEMD decomposition results.

4. Apparatus and application

4.1. The analysis of the rotor misalignment signal
This platform, as shown in figure 2, is mainly consisted of a rotor system and a vibration testing system. The rotor system includes a rotor, a motor, a pair of bearing and a foundation. The vibration testing system includes six groups of eddy current sensors and a set of data acquisition instrument connecting computer. Observing in detail, sensors 1–4 are divided into two groups for capturing the vibration signals located in the cross section with the directions of 45° and 135°. Sensor 5 is used to measure the phase and sensor 6 is applied to capture the rotating speed.

![Figure 2. Structure of the rotor test bench.](image)
The rotor test bench is used to simulate the misalignment fault. The sampling rate is set to be 2048 Hz, the sampling number is set as 2048 points, and the rotating speed is set as 4000 rpm. The vibration signal both in time and frequency domain are illustrated in figure 3 and figure 4.

Figure 3. Misalignment signal of the rotor in time domain.

Figure 4. Misalignment signal of the rotor in frequency domain.

The rotor vibration signal and spectrum show that the dominant fundamental frequency component accompanies with the second harmonic component, indicating that the rotor is running with misalignment fault. According to the typical fault recognition process of the rotor system summarized in 2.4, the standard deviation of the calculated signal is 4.26. Therefore, set the initial parameter ε=0.85, N=100, and conduct EEMD on the signal. IMFs are obtained and shown in figure 5.

Figure 5. IMFs of misalignment signal in time domain (ε=0.85).

Figure 6. IMFs of misalignment signal in frequency domain (ε=0.85).

In figure 5, the main vibration modes of the signal are concentrated in IMF3 and IMF4. Thus, FFT is applied to the first six IMFs, and the spectrum of each IMF is shown in figure 6.

As shown in figure 6, IMF1 and IMF2 have broadband characteristics with small amplitude and are mainly concentrated in high frequency area. Therefore, IMF1 and IMF2, which mainly represent noise, can be deleted. Both IMF3 and IMF4 contain the fundamental frequency components of the signal, which shows significant mode aliasing phenomenon. Hence, IMF3 and IMF4 should be selected. However, IMF5 and IMF6 display the low-frequency noise characteristics with weak amplitude, implying the deletion of IMF5 and IMF6. The result demonstrates that there is a strong correlation between IMF3 and IMF4 with mode aliasing. IMF3 and IMF4 are then used for signal reconstruction. The reconstructed signal and its spectrum are shown in figure 7 and figure 8.

Figure 7. Reconstruction of misalignment signal of the rotor in time domain (ε=0.85).

Figure 8. Reconstruction of misalignment signal of the rotor in frequency domain (ε=0.85).

Figure 7 and figure 8 show that the misalignment vibration mode has been extracted, and the high frequency noise is suppressed accompanying with weak low frequency noise. However, it is obvious
that the mode aliasing is significant. Therefore, \( \varepsilon \) can be larger according to that the rotor vibration frequency mainly manifests low frequency property. Tentatively, it is adjusted to be 2.0. EEMD with a new noise amplitude is carried out on the investigated signals. IMFs and its spectrum can be observed in figure 9 and figure 10.

**Figure 9.** IMFs of misalignment signal in time domain (\( \varepsilon=2.0 \)).

**Figure 10.** IMFs of misalignment signal in frequency domain (\( \varepsilon=2.0 \)).

The comparison between figure 5 and figure 9, figure 6 and figure 10 show that IMF3 has the second harmonic component accompanied with a slight basic frequency, while the basic frequency is dominant in IMF4 without the interference from the second harmonic component. IMF5 gives a slight basic frequency component with a weak low-frequency noise. The mode aliasing phenomenon has been improved. Therefore, IMF3, IMF4 and IMF5 are used for signal reconstruction, and the reconstructed signal and its spectrum are shown in figure 11 and figure 12.

**Figure 11.** Reconstruction of misalignment signal of the rotor in time domain (\( \varepsilon=2.0 \)).

**Figure 12.** Reconstruction of misalignment signal of the rotor in frequency domain (\( \varepsilon=2.0 \)).

Compared with figure 7, the fluctuation of the reconstructed signal is relatively higher when \( \varepsilon \) is equal to 2.0. The main reason is that the noise amplitude is too large and there is no obvious difference between the spectrums. Therefore, the fluctuation and change rule of reconstructed signal can be calculated iteratively, and appropriate noise amplitude can be selected. On the base of eliminating mode mixing, it ensures the small change of the reconstructed signal, and the IMF component has a clearer meaning of single vibration mode. At this point, the iterative search is conducted between the range of 0.85~2.0. The orthogonal change of IMF3 and IMF4, and the fluctuation of the reconstructed signals are shown in figure 13 and 14.

**Figure 13.** Orthogonal trend of the selected IMFs.

**Figure 14.** FV trend of the reconstruction signal.

As can be seen from the orthogonality variation rule of IMF, the value of orthogonality generally shows a trend of fluctuation linear decline with the increase of noise amplitude, which is consistent with the rule that the noise enhancement causes the orthogonality between the signals improved. The
fluctuation variation rule of the reconstructed signal was observed further. Taking ε of 1.40 as the dividing line, the fluctuation on the left has a convergence point close to zero. On the right side, except the 1.42 marked red circle, there is no convergence point close to zero, and there is a tendency of increasing fluctuation. The noise amplitude of 2.0 is inconsistent with the selection condition given by the formula (6). Therefore, 1.42 marked red circle is the critical value reflected in the figure, and this point also corresponds to the 1.42 extreme value point of the marked red circle in the graph of the orthogonal fluctuation change rule. At this point, it can be judged that when ε is equal to 1.42, the orthogonality of components is guaranteed and the signal fluctuation of reconstruction changes little. The obtained IMFs and spectrum are shown in figure 15 and 16.

Figure 15. IMFs in time domain (ε=1.42).

Figure 16. IMFs in frequency domain (ε=1.42).

Figure 15 and 16 show that the mode aliasing of basic frequency has been suppressed to half of the result whose ε is 0.85, which ensures the independent extraction of vibration mode. Moreover, the basic frequency component of IMF5 is extremely small and can be ignored. The reconstructed signal and spectrum with the selected IMF3 and IMF4 are shown in figure 17 and figure 18.

Figure 17. Reconstruction of misalignment signal of the rotor in time domain (ε=1.42).

Figure 18. Reconstruction of misalignment signal of the rotor in frequency domain (ε=1.42).

Figure 17 and figure 18 show the extracted main misalignment mode. The high frequency noise is eliminated, and the fluctuation of the time-domain signal is less than that of the case of 2.0. The results show that by introducing the FV index, the qualitative learning process of traditional EEMD noise amplitude can be transformed into the quantitative learning process, leading to a clear physical significance of the signal components.

4.2. Fault signal analysis of bearing inner ring

EFPEEMD is verified by the fault signal of the bearing inner ring simulated on a bearing test bench from Case Western Reserve University as shown in figure 19.

Figure 19. Structure of the bearing test bench.
The bearing test bench consists of a 2 hp motor (left), a torque transducer/encoder (center), a dynamometer (right), and control electronics. The test bearings support the motor shaft. Single point faults were introduced to the test bearings using electro-discharge machining with fault diameters of 7 mils, 14 mils, 21 mils, 28 mils, and 40 mils (1 mil=0.001 inches). Here, the 6205-2RS JEM SKF, deep groove ball bearing whose inner race has fault diameters of 21 mils is employed. The corresponding defect frequency is 5.41 Hz. Moreover, the sampling frequency is 12 kHz, the sampling length is 122136 and the rotating frequency is 1797 rpm. As a result, the feature frequency of the inner ring is 162.03 Hz. The vibration signal both in time and frequency domain are respectively shown in figure 20 and figure 21.

**Figure 20.** Inner ring defect signal of the bearing in time domain.  
**Figure 21.** Inner ring defect signal of the bearing in frequency domain.

The signal of bearing inner ring and its spectrum show the frequency of 162 Hz of bearing vibration and the frequency modulation of high harmonics. However, the rotating frequency is not obvious. The signal envelope and EFPEEMD are used to decompose the signal, and the effects of IMF in time domain and frequency domain are obtained in figure 22 and figure 23.

**Figure 22.** EFPEEMD IMFs of Inner ring defect signal of the bearing in time domain.  
**Figure 23.** EFPEEMD IMFs of Inner ring defect signal of the bearing in frequency domain.

In figure 22 and figure 23, we can obtain the defect feature frequency of the inner ring and the rotating frequency in IMF6 and IMF9, respectively. The amplitude of 162 Hz component is 0.002154 m.s⁻², and the amplitude of 30 Hz component 0.005143 m.s⁻². Here, we use the two variables to compare the effect between EFPEEMD and EEMD.

In figure 24 and figure 25, the defect feature frequency of the inner ring and the rotating frequency are also located in IMF6 and IMF9. Moreover, the amplitude of 162 Hz component is 0.002122 m.s⁻², and the amplitude of 30 Hz component 0.005137 m.s⁻². As a result, the feature extraction capability of EFPEEMD is higher than that of EEMD, while the difference is small. It may attribute to the much more complexity of the bearing signal than that of the rotor signal.
Figure 24. EEMD IMFs of Inner ring defect signal of the bearing in time domain.

Figure 25. EEMD IMFs of Inner ring defect signal of the bearing in frequency domain.

5. Conclusions
FV index was developed to realize the quantitative calculation of the EEMD noise amplitude, which provides an efficient method to deal with problem of mode aliasing. EFPEEMD is significantly better than EEMD on the analysis of the rotor misalignment fault. The bearing signal is much more complex than the rotor signal, which causes the result of EFPEEMD close to that of EEMD. There are still several aspects that we can pursue to further improve the diagnostic performance. 1) Intelligent optimization algorithm can be attempted to search a suitable noise amplitude by iterating FV indicator. The flow should be investigated. 2) With the well-separated IMFs, the running condition of rotating machinery can be identified by adding deep learning to establish the mapping relation.

References
[1] Chen BQ. Overcomplete Frame Expansion Based on Wavelet Tight Frame and its Applications to Machinery Fault Detection and Diagnosis[D]. Xi'an: Xi'an Jiaotong University Press, 2013.
[2] Feng ZP, Chen XW. Adaptive iterative generalized demodulation for nonstationary complex signal analysis: Principle and application in rotating machinery fault diagnosis[J]. Mechanical Systems and Signal Processing, 2018, 110.
[3] Zhao HY, Wang JD, Jay L, et al. A compound interpolation envelope local mean decomposition and its application for fault diagnosis of reciprocating compressors[J]. Mechanical Systems and Signal Processing, 2018, 110.
[4] Huang NE, Shen Z, Long SR, et al. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis[J]. Proceedings of the Royal Society of London Series A: Mathematical, Physical and Engineering Sciences, 1998, 454 (1971): 903-995.
[5] He ZJ, Zi YY, Zhang XN. Modern signal processing and engineering application[M]. Xi'an: Xi'an Jiaotong University Press, 2007.
[6] Yu DJ, Cheng JS, Yang Y. Application of EMD method and Hilbert spectrum to the fault diagnosis of roller bearings[J]. Mechanical Systems and Signal Processing, 2005, 19 (2): 259-270.
[7] Gai GH. The processing of rotor startup signals based on empirical mode decomposition[J]. Mechanical Systems and Signal Processing, 2006, 20 (1): 222-235.
[8] Liu B, Riemenschneider S, Xu Y. Gearbox fault diagnosis using empirical mode decomposition and Hilbert spectrum[J]. Mechanical Systems and Signal Processing, 2006, 20 (3): 718-734.
[9] Huang N, Shen Z, Long SR. A new view of non-linear water waves: The Hilbert Spectrum[M], 2003.
[10] Zhao JP. Study on the Effects of Abnormal Events to Empirical Mode Decomposition Method and the Removal Method for Abnormal Signal[J]. Journal of Ocean University of Qingdao, 2001, 31 (6): 805-814.

[11] Rato RT, Ortigueira MD, Batista AG. On the HHT, its problems, and some solutions[J]. Mechanical Systems and Signal Processing, 2008, 22 (6): 1374-1394.

[12] Hu AJ, Sun JJ, Xiang I. Mode Mixing in Empirical Mode Decomposition[J]. Journal of Vibration, Measurement & Diagnosis, 2011, 31 (4): 429-434.

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

[14] Cao CF, Yang SX, Jiang X. De-noising method for non-stationary vibration signals of large rotating machineries based on ensemble empirical mode decomposition[J]. Journal of Vibration and Shock, 2009, 28 (9): 33-38.

[15] Yu Y, Lang H. Fault diagnosis of rotor rub based on ensemble EMD[C], 2009: 2-144-142-148.

[16] Lei YG, He ZJ, Zi YY. Application of the EEMD method to rotor fault diagnosis of rotating machinery[J]. Mechanical Systems and Signal Processing, 2009, 23 (4): 1327-1338.

[17] Lei YG, Li NP, Lin J, et al. Fault Diagnosis of Rotating Machinery Based on an Adaptive Ensemble Empirical Mode Decomposition[J]. Sensors, 2013, 13 (12): 16950.

[18] Chen RX, Tang BP, Lv ZL. Ensemble Empirical Mode Decomposition De-noising Method Based on Correlation Coefficients for Vibration Signal of Rotor System[J]. Journal of Vibration, Measurement & Diagnosis, 2012, 32 (4): 542-546.

[19] Zhang WB, Zhou YI, Zhu JX, et al. A New Rotor Fault Diagnosis Method Based on EEMD Sample Entropy and Grey Relation Degree[J]. Applied Mechanics and Materials, 2013, 347-350: 426-429.