Improvement of empirical mode decomposition based on correlation analysis

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Abstract

Empirical mode decomposition (EMD) is an effective method for analyzing nonlinear and non-stationary signals. However, it can be found that there are two problems in this method. One problem is that it may lead to unnecessary redundant decompositions and bring interferences to the results of the analysis. Moreover, unnecessary decompositions may increase the computational time of the EMD algorithm. Another problem is that a signal belongs to the same one of intrinsic mode functions (IMFs) may be decomposed into other IMF components in EMD method. In order to determine the reasonable number of IMFs and reconstruct the signal belongs to the same IMF, an improved method of empirical mode decomposition based on correlation analysis is proposed in this paper. In this method, a simple but effective stopping criterion was proposed to reduce the number of decompositions and remove undesirable redundant decompositions. In order to avoid over decomposition, we reconstruct the signal belongs to the same IMF by using correlation analysis. Finally, the method we proposed is contrasted with the EMD method by analyzing simulation and real signals. The experimental results indicate that our method is very effective in removing redundant IMFs and the running time of our method is reduced by about 70% compared with EMD method. Meanwhile, a similar or better decomposition results can be obtained compared with the EMD method.

Keywords Empirical mode decomposition (EMD) · Correlation analysis · Stopping criterion · Signal reconstruction · Frequency spectrum analysis

1 Introduction

Signal detection technique is widely used in vibration signal monitoring and fault feature identification. Vibration phenomena [1, 2] are also often encountered in science and have a great effect on vibration utilization engineering [3]. Hilbert-Huang Transform (HHT) [4] is very famous in vibration signal detection and fault diagnosis. HHT has been proved to be an effective approach for nonlinear and non-stationary signal processing. The HHT is mainly composed of the empirical mode decomposition (EMD) and Hilbert spectral analysis (HSA) [5]. Any simulation and real signals can be decomposed into a series of intrinsic mode functions (IMFs) by EMD method. It has been widely

applied in numerous fields including vibration signal analysis, biomedical engineering [6, 7], mechanical fault diagnosis [8–10] and image processing [11]. Although the EMD method has been proved to be very effective and specialized in analyzing complex and non-stationary signals, it still suffers from many difficulties such as end effects [12], mode mixing [13] and lacking of a reliable mathematical theory. Many improved schemes have been proposed to resolve these problems in literatures [12, 14, 15]. However, most of the improvements greatly increase the computational complexity.

EMD method has the shortcoming of mode mixing, which means that one intrinsic mode function (IMF) comprises some signals of widely different scales, or

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a signal of the similar scale appearing in multiple IMF components [16], namely over decomposition. In order to resolve this problem, Huang et al. [17] proposed a subjective intermittence test algorithms. However, the method is influenced to a great extent by the selection of scale [16]. Deering and Kaiser [18] proposed a masking signal-added method to solve the problem of mode mixing, in which the extrema of analyzed signal was homogenized distribution. However, it is difficult to choose a suitable masking signal in this method. Wu and Huang [16] proposed a method called ensemble EMD (EEMD) to solve the problem of mode mixing, in which white noise was added to the initial data. Indeed, the EEMD method is a great improvement on the EMD and it can better enhance the robustness of the EMD algorithm. Of course, the IMFs resulting from EEMD algorithm are obviously interfered by the assisted noise. Besides, another method was proposed by Tang et al. [19] to restrain mode mixing by utilizing an optimal morphological filter to restrain the noise. The method was proved to be very effective in dealing with synthetic time series. Considering that the EEMD method has no adaptability and needs manual intervention, an enhanced EEMD method named complementary EEMD (CEEMD) was proposed in literature [20], in which noises were added into the original data in pairs with opposite signs. Compared with EEMD, the superiority of CEEMD is that it can eliminate the residual noise in reconstructing the initial signal when it has the same decompose results as EEMD. However, how to choose the appropriate amplitude and number of added noise is very difficult in both CEEMD and EEMD. Meanwhile, the number of pseudo components will be under the influence of the number of trials and the size of added noises. Moreover, the IMFs got from EEMD and CEEMD sometimes do not meet the IMF definition and the empirical post processing is need in some cases [10].

EMD method also has the problems of decomposition accuracy and efficiency. When a signal belongs to the same IMF is decomposed into other IMF components, which may produce interference to the analysis results and have a bad effect on the decomposition accuracy. Meanwhile, generation of redundant components may increase computation complexity and reduce decomposition efficiency. Motivated by this, the paper dedicates to propose an improvement method based on EMD, in which correlation coefficients between every IMF and the investigated signal are taken into consideration.

The rest of this paper is organized as follows. The EMD method is introduced briefly in Sect. 2. In Sect. 3, the novel signal processing method is proposed. In Sect. 4, comparative studies of the method we proposed and the EMD method are performed by analyzing two kinds of simulation signals. In Sect. 5 our method is applied to the experimental

data of rolling element bearing with fault. Finally, conclusions are drawn in Sect. 6.

2 Overviews of EMD

EMD is an adaptive approach which was introduced by Huang et al. [4]. Using this method, an investigated signal $x(t)$ ($t > 0$) can be decomposed into a number of IMFs through sifting processes, and each of IMFs should satisfy the following sifting criterion,

1. The number of zero-crossings and extrema must be equal or only a difference of one in the whole dataset.
2. The mean value of the local minima envelope and the local maxima envelope must be equal to zero at any point.

An investigated signal $x(t)$ can be decomposed as follows by using EMD algorithm [6].

Step 1 Identify all local extrema and connect the sequential local maxima to form the upper envelope by using cubic spline.

Step 2 Connect all local minima to derive the lower envelope using the same way.

Step 3 Calculate the average of upper and lower envelopes, namely $m_1(t)$, extract the first proto-mode $h_1(t)$:

$$h_1(t) = x(t) - m_1(t) \quad (1)$$

Step 4 If $h_1(t)$ does not satisfy the definition of IMF, replace the investigated signal $x(t)$ with $h_1(t)$ and repeat steps 1–3, then we can get the proto-mode $h_{11}(t)$:

$$h_{11}(t) = h_1(t) - m_{11}(t) \quad (2)$$

where $m_{11}(t)$ represents the average of lower and upper envelopes. Repeat the sifting process k times until the stopping criterion is satisfied, then $h_{1k}(t)$ is treated as an IMF, and it can be given by

$$h_{1k}(t) = h_{1(k-1)}(t) - m_{1k}(t) \quad (3)$$

And the IMF can be expressed as follows:

$$c_1 = h_{1k}(t) \quad (4)$$

The most widely applied type of stopping criterion is to set the value of standard deviation (SD). The SD of two successive sifting operations is defined as the following formulas:

$$SD = \sum_{t=0}^T \frac{|h_{k-1}(t) - h_k(t)|^2}{h_{k-1}^2(t)} \quad (5)$$

Step 5 Compute the residue from the $x(t)$:

$$r_1(t) = x(t) - c_1(t) \quad (6)$$

Then the residual $r_1(t)$ is regarded as a new signal and has to repeat the steps 1–5 until it meets the stopping conditions including that the residue is monotonic or with a neglectable energy rate to the investigated signal $x(t)$. Thus, the initial signal $x(t)$ can be given by

$$x(t) = \sum_{i=1}^n c_i(t) + r_n(t) \quad (7)$$

where $r_n(t) = r_{n-1}(t) - c_n(t)$. As can be seen from the above analysis that a complex signal is decomposed into finite IMFs and a residue $r_n(t)$. The empirical mode $c_i(t)$ represents different frequency bands, and it will change for different investigated signals. Therefore, some physical meanings hidden in the original signals can be revealed used the EMD method.

3 The proposed method based on correlation analysis

3.1 The problem of redundant decompositions in EMD method

In order to illustrate this problem, a simulation signal is described as follows:

$$\begin{aligned} x_1(t) &= (1 + 0.5 \sin 2\pi 2.5t) \cos(2\pi 125t \\ &\quad + 2\pi 10t^2), \quad x_2(t) = 4 \sin 2\pi 20t \\ x(t) &= x_1(t) + x_2(t); \quad t = 0 : 1/1000 : 1 \end{aligned} \quad (8)$$

Without loss of generality, the investigated simulation signal $x(t)$ is composed of an amplitude and frequency modulated signal and a sinusoidal signal. The time domain waveforms of $x(t)$, $x_1(t)$ and $x_2(t)$ are shown in Fig. 1. The EMD method is used to decompose the signal $x(t)$ into a set of IMFs which are illustrated in Fig. 2. It can be seen in Figs. 1 and 2 that the original simulation signal $x(t)$ is only composed two signals while the number of IMFs is five by using the EMD method. Obviously the components of IMF3, IMF4 and IMF5 are the redundant decompositions and these decompositions are undesirable. The phenomenon can be verified by the correlation analysis between every IMF and the original signal. Table 1 shows the correlation coefficients [5, 6] between the decomposed IMFs and the original signal. Signal correlation analysis is used to study the correlation between two signals and the degree of closeness they are closely related to each other. The correlation coefficient is a quantity used to describe the degree of correlation between two signals. The values of correlation coefficient are from range of 0 to 1. The closer the correlation coefficient is to 0, the weaker the correlation between signals is. The closer the correlation coefficient is to 1, the stronger the correlation between signals is. It can be found in Table 1 that the correlation coefficient between $x(t)$ and IMF1 is 0.2724, the correlation coefficient between $x(t)$ and IMF2 is 0.9565 while the correlation coefficient is sharply reduced to 0.0462 since IMF3. This phenomenon suggests that the components IMF3–IMF5 are the redundant decompositions and should be regarded as residues.

Fig. 1 The waveforms of $x(t)$ and its components

Fig. 2 Decomposition results of signal $x(t)$ using EMD **Table 1** Correlation coefficients between signal $x(t)$ and each IMF extracted via EMD

The decomposed IMF	IMF1	IMF2	IMF3	IMF4	IMF5
Correlation coefficient	0.2724	0.9565	0.0462	0.0325	0.0254

3.2 A signal belongs to the same IMF may be decomposed into other IMF components in EMD method

Consider a simulation signal defined by the following form:

$$y(t) = y_1(t) + n(t), \quad t \in [0, 1] \quad (9)$$

where $y_1(t) = \sin(60\pi t)$, $n(t)$ is a white noise with signal to noise ratio of 15. So the signal $y(t)$ is composed of a sinusoidal signal and a white noise. The time-domain waveforms of $y(t)$, $y_1(t)$ and $n(t)$ are depicted in Fig. 3. The EMD method is used to decompose the signal $y(t)$ into several IMFs which are shown in Fig. 4. It can be found in Figs. 3 and 4 that the original signal $y(t)$ is composed of a signal and a white noise while the number of decomposed IMFs is six by the EMD method. And the IMF2 and IMF3 have similar waveform. In view of this, a new signal IMF2n can be got by reconstructing IMF2 and IMF3 (Reconstruction

formula seen in formula (14)). The waveforms of IMF2, IMF3 and IMF2n can be seen in Fig. 5 and there is a big difference in waveform amplitudes. The amplitude range of IMF2 is from -3 to 3 while the amplitude range of IMF3 is from -2.2 to 2.2 and they both have a relatively larger errors compared with $y_1(t)$ whose amplitude range is from -1 to 1 . However, the amplitude range of IMF2n is from -1.2 to 1.2 which is close to that of $y_1(t)$. This demonstrates that IMF2n can be approximately regarded as signal $y_1(t)$. Meanwhile, the decomposed components after IMF3 can be regarded as redundant decompositions. In order to prove the rationality of our idea, the frequency spectra of $y_1(t)$, IMF2, IMF3 and IMF2n are described in Fig. 6. In which we can see that the frequency spectrum of IMF2n coincide well with that of $y_1(t)$ and the IMF2n can better reflect the characteristics of the original signal, while the frequency spectra of IMF2 and IMF3 have larger errors compared with that of IMF2n. The phenomenon can be revealed by the correlation analysis between every IMF and the investigated signal. The correlation coefficients between the decomposed IMF and the original signal are listed in Table 2. It can be observed in Table 2 that the correlation coefficient between $y(t)$ and IMF2 is 0.6068, the correlation coefficient between $y(t)$ and IMF3 is 0.7496 while the correlation coefficient is sharply reduced to 0.0007 since IMF4.

Fig. 3 The waveforms of $y(t)$ and its components **Fig. 4** Decomposition results of signal $y(t)$ using EMD

This means that the decomposed components IMF3–IMF7 are the redundant decompositions and should be treated as residues. Owing to the correlation coefficients of IMF2 and IMF3 relative to the original signal are close to each other (A criterion can be used to determine whether the two values are close to each other in Sect. 3.3.2), they can

be regarded as the same signal while decomposed into two IMF components. However, a key problem has been neglected that the correlation coefficient between $y(t)$ and IMF1 is only 0.0726. Owing to the fact that it appears before IMF2 and IMF3, IMF1 can be considered as a physical meaning signal such as the white noise.

Fig. 5 The waveforms of IMF2, IMF3 and IMF2n **Fig. 6** The frequency spectra of $y_1(t)$, IMF2, IMF3 and IMF2n **Table 2** Correlation coefficients between signal $y(t)$ and each IMF extracted via EMD

The decomposed IMF	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6
Correlation coefficient	0.0726	0.6068	0.7496	0.0007	0.0002	0.024

3.3 The proposed method in this paper

3.3.1 An approach to the solution of removing redundant decompositions

As discussed in Sect. 3.1, the original signal $x(t)$ is

composed of signal $x_1(t)$ and a signal $x_2(t)$, where $x_1(t)$ is a amplitude and frequency modulated signal and $x_2(t)$ is a sinusoidal signal. The EMD decomposed results IMF3–IMF5 are the redundant decompositions and these decompositions are undesirable. The cause of this phenomenon is the stopping criterion in Eq. (5) that is used

to limit the standard deviation of two successive sifting operations. The EMD method is not based on rigorous mathematical theory and residual signals are more likely to appear in the sifting process. Generation of residual components may bring interferences to the analysis results and impede the computational efficiency of the algorithm. The proposed approach can remove the redundant IMFs and retain the physical meaning signals, in which correlation coefficients between each IMF and the original signal are taken into consideration. In the proposed method, the decomposition operations are stopped when the correlation coefficient [5, 6] between two adjacent IMFs satisfy formulas (10)–(12). The formulas are defined by the following form:

$$\text{Coef}(\text{IMFi}) \times 10^a \geq 1 \quad (i = 1, 2, \dots, a \in N^+) \quad (10)$$

$$\text{Coef}(\text{IMFj}) \times 10^b \geq 1 \quad (j = i + 1, 2, \dots, b \in N^+) \quad (11)$$

$$\text{Minb} - \text{Mina} \geq 1 \quad (12)$$

where symbol *Coef* represents correlation coefficient between every IMF and the original signal, *Mina* is the minimum value of *a* satisfied formula (10) and *Minb* is the minimum value of *b* satisfied formula (11). In order to illustrate the effectiveness of the proposed approach on removing redundant IMFs and reducing the number of decompositions, we use our method to decompose the signal $x(t)$ in Sect. 3.1 again and the decomposition results are shown in Fig. 7. In which we can see that $x(t)$ is decomposed into IMF1, IMF2 and residue. The IMF1 and IMF2 are physical meaning signals and respectively represent the signal $x_1(t)$ and $x_2(t)$. Meanwhile, the residue amplitude is very small and it is close to zero. The decomposed results

illustrate the availability of the proposed approach in this section.

3.3.2 An approach to the solution of assuring that a signal only appear in the same IMF component

As discussed in Sect. 3.2, the signal $y_1(t)$ is a sinusoidal signal while it is decomposed into IMF2 and IMF3 decompositions. The amplitude range of $y_1(t)$ is from -1 to 1 while the amplitude range of IMF2 is from -3 to 3 and the amplitude range of IMF3 is from -2.2 to 2.2 . Obviously the decomposition results are not accurate enough and inconvenient to analysis results. The proposed approach is aimed at reconstructing the signal by combining the signals which are part of the same signal while decomposed into different IMFs. In this approach, we use a judgment criterion to confirm whether each IMF belongs to the same signal or not. The judgment criterion is defined by the formula (13) and the signal reconstruction formula is defined by the formula (14):

$$\begin{aligned} & ||\text{Coef}(\text{IMFi})| - |\text{Coef}(\text{IMFj})|| \\ & \leq \frac{1}{n} |\max|\text{Coef}(\text{IMFi})| - \min|\text{Coef}(\text{IMFi})|| \end{aligned} \quad (13)$$

$$\begin{aligned} \text{IMFi} = & \left(\frac{\text{Coef}(\text{IMFi})}{\text{Coef}(\text{IMFi}) + \sum_{k=1}^{\max_j} \text{Coef}(\text{IMFk})} \right) \text{IMFi} \\ & + \sum_{k=1}^{\max_j} \left(\frac{\text{Coef}(\text{IMFk})}{\text{Coef}(\text{IMFi}) + \sum_{k=1}^{\max_j} \text{Coef}(\text{IMFk})} \right) \text{IMFk} \end{aligned} \quad (14)$$

where $i = 1, 2, 3, \dots$ is the index of IMFs, $j = i + 1$, n is the maximum of the index.

Fig. 7 Decomposition results of signal $x(t)$ using the proposed approach

The effectiveness of the proposed approach can be found in Figs. 5 and 6 in Sect. 3.2. In Fig. 5 we can see that IMF2n is reconstructed using IMF2 and IMF3 by the proposed approach, and its waveform is closer to the sinusoidal signal $y_1(t)$ than IMF2 and IMF3. In Fig. 6 we can clearly see that the frequency spectrum of IMF2n can better reflect the characteristics of signal $y_1(t)$ while there are larger errors in IMF2 and IMF3.

Flowchart of the proposed empirical mode decomposition method based on correlation analysis is illustrated in Fig. 8, and the main operation procedures are listed as follows:

Step 1 Compute IMF_i from the vibration signal $x(t)$ using the iteration process that introduced in Sect. 2, where $i=1,2,3,\dots$ is the index of IMFs.

Step 2 Calculate the correlation coefficient $\text{Coef}(\text{IMFi})$ between IMF_i and $x(t)$.

Step 3 Remove the IMF_i from $x(t)$ and get the residual signal $r_i(t)$.

$$r_i(t) = x(t) - \text{IMFi} \quad (15)$$

Step 4 Replace the original signal $x(t)$ with $r_i(t)$ and repeat from step 1 to step 3 until the iteration process satisfy $\text{Minb} - \text{Mina} \geq 1$ or $\text{SD} < 0.1$.

Step 5 Reconstruct IMF_{in} using the Eq. (14).

To demonstrate the effectiveness of the proposed algorithm, we make experiments on the simulation and real signals next. All of the experiments in this paper are made in a machine with 2 GBs of memory and Intel(R) Core(TM) i5-2520M CPU, running 32 bit Windows 7 operating system, and the MATLAB version is 7.7.0.

4 Simulation signal analysis

In order to verify the validity of the proposed method, without loss of generality, we consider a simulation signal defined as follows:

$$x_1(t) = e^{-t} \cos 48\pi t, \quad x_2(t) = (t+1) \cos 20\pi t, \quad x_3(t) = \cos 8\pi t$$

$$x(t) = x_1(t) + x_2(t) + x_3(t); \quad t = 0 : 1/1000 : 1 \quad (16)$$

where $x(t)$ is composed of three signals and their waveforms are depicted in Fig. 9. Then the mixed signal $x(t)$ is

Fig. 8 Flowchart of the proposed method

Fig. 9 The waveforms of $x(t)$ and its components **Fig. 10** Decomposition results of signal $x(t)$ using EMD

decomposed using EMD and our method respectively and the decomposition results can be seen in Figs. 10 and 11.

By EMD and our method the signal $x(t)$ can be rightly decomposed to three components just as shown in Figs. 10 and 11. However, the number of IMFs is four using EMD while it is three using our method, and the IMF4 component produced by EMD method is bad for result analysis. So the proposed method is superior to EMD in decomposition accuracy.

Next, we consider another simulation signal mentioned in the literature [21], which is composed of two sinusoidal FM signals and one Gaussian wave packet. The waveforms of the simulation signal and its components are depicted in Fig. 12. Figure 13 shows the decomposition results using EMD method and Fig. 14 shows our decomposition results.

It can be easily found in Figs. 12 and 14 that the three IMFs extracted from the original signal by our method can reflect the compositions of the original signal. Table 3

Fig. 11 Decomposition results of signal $x(t)$ using our method

Fig. 12 The waveforms of signal and its components

shows the numbers of decomposed IMFs and time consuming of EMD and our method, in which we can see that our method not only removes the redundant IMFs but also reduce the calculation time.

5 Engineering application

In order to detect the effectiveness of the proposed algorithm, we apply this method to local outer and inner race fault of rolling element bearing. And the experimental

data are obtained from Bearing Data Center of Case Western Reserve University [22, 23]. As shown in Figs. 15 and 16, the test stand consists of a zero hp motor (left), a torque transducer (center), a dynamometer (right) connected by a self-aligning coupling (center). The test bearings support the motor shaft at the driving end. Single point faults were introduced to the test bearings using electro-discharge machining with fault diameters of 0.1778 mm depth of 0.2794 mm. In the course of the experiments, the motor speed was 1797 r/min, the

Fig. 13 Signal decomposition results using EMD

Fig. 14 Signal decomposition results using our method

Table 3 Comparison of two algorithms on simulation signal decomposition

Algorithm	Numbers of IMFs	Time consuming (s)
EMD method	10	0.9834 ± 0.013
Our method	3	0.2864 ± 0.009

Fig. 15 Experiment system **Fig. 16** Experiment schematic diagram**Fig. 17** The waveform of a vibration signal of rolling element bearing with inner race fault

sampling frequency was 12,000 Hz and the sample time was 0.25 s.

First of all, an acceleration vibration signal is chosen to handle, which are derived from a rolling element bearing with inner race fault. And its waveform is depicted in Fig. 17. The rotational frequency of the motor shaft f_r is about 30 Hz when the speed of the rotating shaft is 1797 r/min, and the fault feature frequency f_i is about 162 Hz.

To compare the decomposition effects of the two algorithms, the signal shown in Fig. 17 is decomposed using EMD and our method, and the number of IMFs is ten and three respectively. Given this article's space limitations, their time domain decomposing results are omitted while their envelope spectra are plotted in Figs. 18 and 19. Considering that the envelope spectra of IMF4–IMF10 don't have much help for the analysis results of EMD method, only the first six envelope spectra of IMFs are given in Fig. 18. The following results can be easily obtained in Figs. 18 and 19. In the first place, the fault frequency

Fig. 18 The envelope spectra of IMF components obtained from EMD **Fig. 19** The envelope spectra of IMF components obtained from our method

($f_i = 162$ Hz) and twice rotational frequency ($2f_r = 60$ Hz) can be clearly seen in Figs. 18a–c and 19a–c, which indicates that the twice rotational frequency is a modulated signal to the fault frequency. Consequently, the inner race fault diagnosis can be achieved. In addition, the spectrum line in 100 Hz in Figs. 18a and 19a is unaccountable and

Table 4 Comparison of two algorithms on real signal decomposition

Algorithm	Numbers of IMFs	Time consuming (s)
EMD method	10	0.5962 ± 0.0039
Our method	3	0.2006 ± 0.0013

will causes disturbing influence to the rotating frequency analysis. In the next place, the fault frequency ($f_i = 162$ Hz), twice fault frequency ($2f_i = 324$ Hz) and twice shaft frequency ($2f_r = 60$ Hz) can be easily observed in Figs. 18b and 19b, through which the inner race fault diagnosis can be achieved too. Thirdly, in Fig. 18d–f we can see that the envelope spectra have no physical meaning and they are redundant decompositions. Table 4 shows the proposed method not only removes the redundant IMFs but also increase the calculation speed, meanwhile, we can obtain the similar decomposing performance compared with EMD method.

Another vibration signal stems from a bearing with outer race fault, in which sampling frequency, shaft rotating speed and sampling time are the same as the inner race fault mentioned above. Figure 20 shows the waveform of this signal. The motor shaft frequency f_r is about

30 Hz, and the fault frequency of outer race f_o is about 107 Hz.

Firstly, this signal is decomposed using EMD and our method, and the number of IMFs obtained are eleven and four respectively. In view of the space limitations of this paper, their time domain decomposing results are omitted while their envelope spectra are depicted in Figs. 21 and 22. Owing to the fact that the envelope spectra of IMF5–IMF11 don't have much help for the analysis results of EMD method, only the first six envelope spectra of IMFs are given in Fig. 21. In Figs. 21a and 22a we can easily observe the fault frequency ($f_o = 107$ Hz), twice fault frequency ($2f_o = 214$ Hz), thrice fault frequency ($3f_o = 321$ Hz), quadruple fault frequency ($4f_o = 428$ Hz) and rotational frequency ($f_r = 30$ Hz), which indicates that the rotational frequency is a modulated signal to the fault frequency. In practice, the outer race fault diagnosis can be obtained

Fig. 20 The waveform of a vibration signal of rolling element bearing with outer race fault

Fig. 21 The envelope spectra of IMF components obtained from EMD

Fig. 22 The envelope spectra of IMF components obtained from the proposed method **Table 5** Comparison of two algorithms on real signal decomposition

Algorithm	Numbers of IMFs	Time consuming (s)
EMD method	11	1.6958 ± 0.0031
Our method	4	0.4645 ± 0.0011

using EMD and our method. However, the thrice fault frequency ($3f_o = 321$ Hz) in Fig. 21b is not clear while it is very clear in Fig. 22b. And the shaft frequency ($f_r = 30$ Hz) in Fig. 21c can't be distinguished while it can be easily found in Fig. 22c. In addition, the envelope spectra in Fig. 21e–f have no physical meaning and they are redundant decompositions. Table 5 shows the proposed method not only removes the redundant IMFs but also increase the calculation speed, and we can obtain the similar or even better decomposing performance compared with EMD method.

6 Conclusions

This paper proposed an improved method of empirical mode decomposition based on correlation analysis to remove the redundant IMFs of EMD and reconstruct the signal belongs to the same IMF. Comparative studies show

that the proposed method is superior to EMD method in decomposition efficiency, and the running speed of our method is about three times that of EMD. Moreover a similar or even better decomposing performance can be obtained compared with EMD. From the decomposed results of simulation signals, we can see that the proposed method is very effective in dealing with the situation of over decomposition. In addition, the proposed method is more efficient than EMD method in decomposition speed and the high decomposition efficiency makes it as an alternative way for on-line fault monitoring. The more complex the vibration signal and the more components the signal is composed of, the more obvious the superior performance of our method is. However, there are still some issues that need to be explored in depth, such as the threshold of stopping criterion based on correlation coefficient. In the future work we will focus on finding a more appropriate threshold through theoretical analysis and experiment.

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Compliance with ethical standards

Conflict of interest All authors have checked the manuscript and have agreed to the submission. And all authors declare that they have no conflict of interest.

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