An algorithm to remove noise from locomotive bearing vibration signal based on self-adaptive EEMD filter and its application in the fault diagnosis

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Abstract: This paper describes an improved ensemble empirical mode decomposition (EEMD) algorithm, in which the sifting and ensemble number are self-adaptive. In particular, the new algorithm can effectively avoid the mode mixing problem. The algorithm has been validated with a simulation signal and locomotive bearing vibration signal. The results show that the proposed self-adaptive EEMD algorithm has a better filtering performance compared with conventional EEMD. The filter results further show that the feature of the signal can be distinguished clearly with the proposed algorithm, and which implies that the fault characteristics of locomotive bearing can be detected successfully.

Key words: locomotive bearing, vibration signal enhancement, self-adaptive EEMD, parameter-varying noise signal, feature extration

Nomenclature

x original signal
u extreme envelope
m average value
n noise signal
c IMF component
r residue signal
N number of the IMF
L signal length
P sifting number
f sampling frequency
e amplitude

Abbreviations

EMD empirical mode decomposition
IMF intrinsic mode function
EEMD ensemble empirical mode decomposition
SD standard deviation

Superscripts

th added noise

Subscripts

i component

1 Introduction

With economic and social developments in modern times, the need for railway transportation capability has been increasing considerably [1]. The railway transportation has been playing a critical role, and its faults would cause significant casualties and property losses [2-3]. To ensure a safety, fluid and efficient traffic circulation, it is of importance to diagnose the status of trains in terms of the train bearing. In the locomotive driving system, the whole weight of the locomotive is supported by the bearings. When the locomotive is running, the bearings also spin at a very fast speed. Thus, the health of the bearings is very important for the continuous, safe and stable operation of locomotives. In consequence, more effective algorithms are needed to diagnose locomotive bearing conditions [4].

Signal processing technique is one of the primary means of fault diagnosis, which relies on the signal released from the diagnostic objectives, like vibration signal released from rotating machinery [5-7]. Empirical mode decomposition (EMD) [8-9] is one of popular algorithms used for non-stationary and nonlinear signal processing, which is widely used for fault diagnosis and feature extraction of different kinds of rotating machinery [10-11]. In EMD algorithm, it decomposes a non-stationary signal into of a series of signals, also known as intrinsic mode function (IMF) [12-13], which are composed of different frequencies and a trends signal. The typical characteristics of EMD algorithm are adaptive, orthogonally and completeness, which means that the IMFs are determined by the characteristics of the signal instead of predetermined algorithms. However, EMD algorithm still has some problems, like mode mixing [14], stop condition [15], the end effect [16]. For mode mixing, its existence in IMF components is due to the facts that single IMF contains a widely disparate scales of components and components have a similar scale residing [17-18].

In order to solve the mode mixing problem existed in EMD algorithm, ensemble empirical mode decomposition (EEMD), an ameliorative algorithm of EMD, was proposed to improve the performance of EMD algorithm in mode mixing problem. EEMD algorithm is also a signal decompose algorithm, but it is noise-assisted. With plus finite white noise whose average value is zero into the vibration signal that is need to be processed, EEMD algorithm is expected to solve the mode mixing problem that exists in EMD algorithm to some extent [19]. However, the decomposing effect of EEMD algorithm relies on the parameters of the while noise and sifting number utilized in the EEMD algorithm, which is included in the amplitude and the frequency of the white noise, the sifting and the ensemble number etc. Usually, the parameters of EEMD algorithm are set up as constant values in most instances. However, different kinds of frequency components existed in the vibration signal have different sensitivities to the chosen parameters [20]. Consequently, mode mixing problem still

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exists and the decomposition capacity of EEMD algorithm needs to be improved in other ways, like change parameters used in EEMD algorithm.

According to the relationship between the decomposing behavior of EEMD algorithm and the decomposed results of different IMFs with different frequencies, this paper aims to propose an ameliorative EEMD algorithm with self-adaptive parameters and compare its performances with conventional EEMD algorithm on the mode mixing problem in the feature extraction of vibration signal and fault diagnosis for locomotive bearing.

2 Fault diagnosis system design and vibration signal process methods

2.1 Fault diagnosis system design

In this study, a signal process algorithm was developed for train bearing fault detection through vibration signal analysis, and it is expected to deliver a design of fault diagnosis system for locomotive driving system. The proposed scheme for locomotive bearing fault diagnosis is shown in Figure 1.

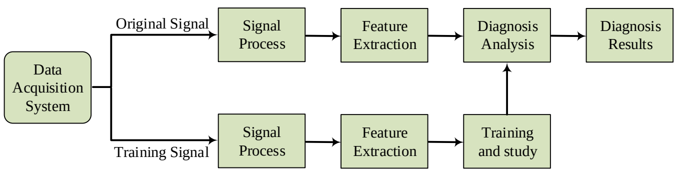

Fig 1. Proposed scheme for locomotive bearing fault diagnosis

In the proposed scheme, there are two sets of vibration signals of the locomotive obtained by the data acquisition system. The training data is used to train and study to get the feature of the fault bearing corresponding to the fault type, the original data is used to diagnose the fault to get the fault type of the bearing. The sampled vibration signals (original and training) are first processed to filter the noisy signal, and followed by feature extraction. Then the training and study signal is used to analysis the original signal and further diagnosis the fault of the bearing. It can be seen that signal process is not only a basic step but also a necessary step for fault diagnosis, and the filtering effect determines the precision of diagnosis results.

2.2 EMD analysis

EMD method is essentially a algorithm of "screening" data [17-18], and it is capable to decompose a vibration signal into a series of IMFs, which meet the following two conditions: (1) The number of zero-crossing and the number of extrema must be the same or differ by one at most in the entire data set; (2) Throughout the signal curve, the mean value of the envelope defined by the local minima and the envelop defined by the local maxima are zero. The original EMD is based on the characteristic time scale which defined by the extreme [21]. It is well known that EMD is used for sifting process. The procedure of the EMD algorithm can be summarized as follows.

Step 1: Marking the original signal as $x(t)$, and find all the local maxima and the minima of the signal.

Step 2: Connect the maxima to form a curve as the upper envelope $u_{max}(t)$; then the same with the minima to form a curve as the lower envelop $u_{min}(t)$. Then identify the average value, $m(t)=\left(u_{max}(t)+u_{min}(t)\right)/2$.

Step 3: Extract the remain signal $h_1(t)$, $h_1(t)=x(t)-m(t)$, and if $h(t)$ meets the two conditions of the IMF, then the $h_1(t)$ is regarded as the first IMF component. Otherwise, repeat the same process until the *k* iterations from step 1 to 3 until $h_1(t)$ meets the IMF's conditions, then $c_1(t)=h_k(t)$. Stopping criteria (standard deviation, *SD*) are used in this study, such as:

$$\sum_{t=0}^{T}\frac{\left|h_{k-1}(t)-h_k(t)\right|^2}{h_{k-1}^2(t)}\le SD \tag{1}$$

Generally, the *SD* value is set between 0.2 and 0.3, which is called standard deviation.

Step 4: The first IMF component $c_1(t)$ is separated from the original signal $x(t)$, then calculate the first residue signal, denote by $r_1(t)$, $r_1(t)=x(t)-c_1(t)$.

Step 5: Take the residual signal as the original signal and repeating the step 1 to 4 to obtain $c_2(t),c_3(t),\cdots,c_n(t)$.

At last we get a collection of all the IMF components and a residue $r(t)$.So the signal $x(t)$ can be expressed as :

$$x(t)=\sum_{i=1}^{n}c_i(t)+r(t) \tag{2}$$

2.3 EEMD analysis

Currently, although EMD algorithm is widely used in the vibration signal process, it still has the problem of mode mixing. To solve this problem, Wu and Huang [17] proposed the EEMD algorithm, which is a kind of noise-assisted data analysis technology. This algorithm defines the IMF components as the mean of an ensemble of trials. Each trial consisted of the decomposed results of the original signal and a white noise with finite amplitude decomposed by EMD algorithm.

The mechanism of how to avoid mode mixing problem in EEMD algorithm is briefly described as follows. In the process, white noise is added into the signal that is need to be decomposed to make the signal continuous in different scale. Due to the statistical characteristics of the white noise, it has no impact on the original signal after repeating average operation. Therefore, the integral mean value can be treated as the final decomposition results.

The specific steps of EEMD algorithm are listed as follows [18]:

Step 1: Add white noise, zero mean and constant amplitude standard deviation, to the original signal, :

$$x_i(t) = x(t) + n_i(t) \tag{3}$$

Where $x_i(t)$ is the signal added with the i^{th} white noise.

Step 2: Decompose $x_i(t)$ using EMD algorithm and obtain the respective IMFs marked as $c_{ij}(t)$ and a residue of data denoted by $r_i(t)$ .Where $c_{ij}(t)$ is the j^{th} IMF after decomposition, which is the i^{th} added white noise to the original signal.

Step 3: Calculate the above corresponding IMFs and finalize them using an ensemble average way.

$$c_j = \frac{1}{N}\sum_{i=1}^{N} c_{ij}(t) \tag{4}$$

Where: $c_j(t)$ represents the j^{th} IMF of EEMD.

The decomposition performance of EEMD highly depends on the selected parameters during the course of EEMD algorithm. Once the parameters in the EEMD changed, the decomposition results might be different accordingly. Fig. 2 is a simulation signal to support the above statement. The signal $x(t)$ can be treated as the superposition of three signals ($x_1(t)$, $x_2(t)$ and $x_3(t)$). $x_1(t)$ is an impact signal, $x_2(t)$ is a high-frequency sinusoidal signal wave, and $x_3(t)$ is a low-frequency sinusoidal signal wave.

The simulation signal is decomposed using EEMD algorithm and during the process different white noises are used. First, the simulation signal is decomposed with the added white noise (amplitude 0.001). The decomposition results are shown in Fig.3 (a) - (d), respectively. The impact signal ($x_1(t)$) and the high-frequency sinusoidal signal ($x_2(t)$) are decomposed into the same IMF c_2, which means that the mode mixing exists and occurs between high frequency components. This can be ascribed to that the added noise is not large enough to change the position of the extreme.

Then, the experimental signal is decomposed using EEMD algorithm with the added white noise (amplitude 0.01, which is the standard deviation). The decomposed results are shown in Fig.4 (a)-(d), respectively. The low frequency sinusoidal signal ($x_3(t)$) is decomposed into IMF c_4, and the signal also has mode mixing problem, which occurs between low frequency components. One of the reasons is that the white noise added into the signal is too large which breaks the extreme distribution of the low frequency signals, and results the mode mixing problem.

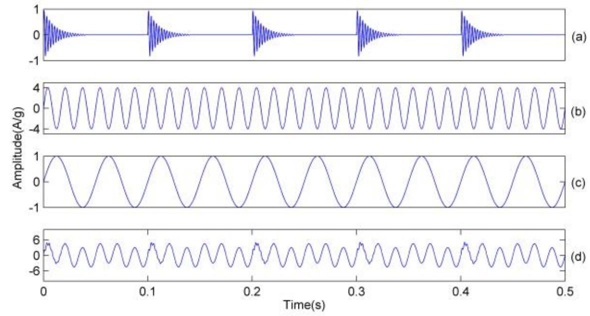

Fig 2. (a-c) the three components $x_1(t)$, $x_2(t)$, $x_3(t)$, and (d) the simulation signal $x(t)$

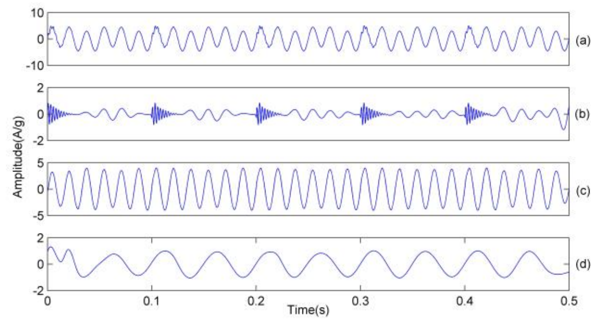

Fig 3. The partial decomposed results with added noise amplitude of 0.001

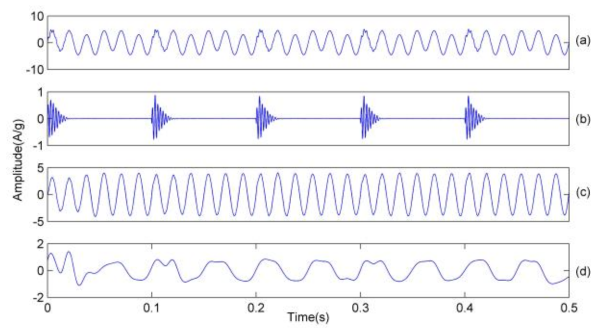

Fig 4. The partial decomposed results with added noise amplitude of 0.01

According to the above experimental results, the conclusion can be drawn is that IMFs with different frequencies have different sensitivities to the white noise added into the simulation signal in the process of the EEMD algorithm. Nevertheless, the EEMD algorithm always imports the white noise with a constant amplitude and sifting number for the IMFs with different frequencies. The problem of mode mixing still exists in the process of EEMD algorithm and the performance of the EEMD algorithm still need to be further improved.

3 The proposed self-adaptive EEMD method

3.1 The Proposed Method

In the proposed algorithm, based on the fact that IMFs with different frequencies have different sensitivities to white noise, different amplitude noises and sifting numbers are used in different frequency components, which means that large noise and great sifting number are used in obtaining high-frequency components, while small noise and small sifting number are used in obtaining low frequency components. In order to meet the criterion of white noise, many types of signal have been tested to find an appropriate noise signal that amplitude changes as a sinusoidal function of the frequency. In this study, such noise signal was used in the proposed algorithm instead of using statical white noise during the EEMD process. Figure 5 shows the constructed sinusoidal signal, here f_s represents the sampling frequency and e represents the amplitude.

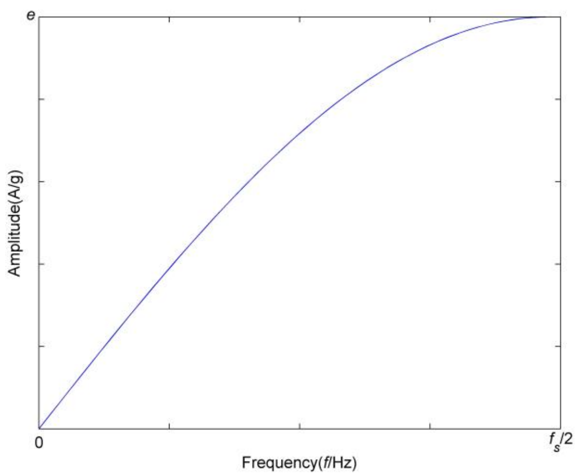

Fig 5. The spectrum of the constructed noise

The flow chart of the self-adaptive EEMD method is shown in Fig.6. The flow chart shows the following detailed procedural steps.

Step 1: Set the original signal as $x(t)$, according to the length of signal. Equation (5) is the number of the IMF [20]:

$$N = \log_2 L - 1 \tag{5}$$

Where L is the signal length.

Step 2: Initialize the number of the ensemble M and the amplitude e of the highest frequency of the added noise, usually, e=0.3 and M=150, let m=1.

Step 3: Calculate the sifting number P_i for the i^{th} IMF component adaptively using Equation (6).

$$P_i = 2^{N-2i} + 2 \text{ , } i = 1, 2, \cdots, N \tag{6}$$

Step 4: Cconstruct the noise signals $n_k(t)$ according to Figure 5, and add the noise signal to the original signal which need to be processed.

$$x_m(t) = x(t) + n_m(t) \text{ , } m = 1, 2, \cdots, M \tag{7}$$

Step 5: Process $x_m(t)$ and obtain a series IMF components using EMD algorithm, namely as imf_{1m} imf_{2m},…, imf_{im}.

Step 6: Repeat the step (4) to step (5) with $m = m+1$ until m=M.

Step 7: calculate the ensemble mean imf_i with the M experimentations for every IMF according to equation (8). Use the mean as the final result of the IMF.

$$imf_i = \frac{1}{M}\sum_{m=1}^{M} imf_{im} \text{ , } i = 1, 2, \cdots, N, m = 1, 2, \cdots, M \tag{8}$$

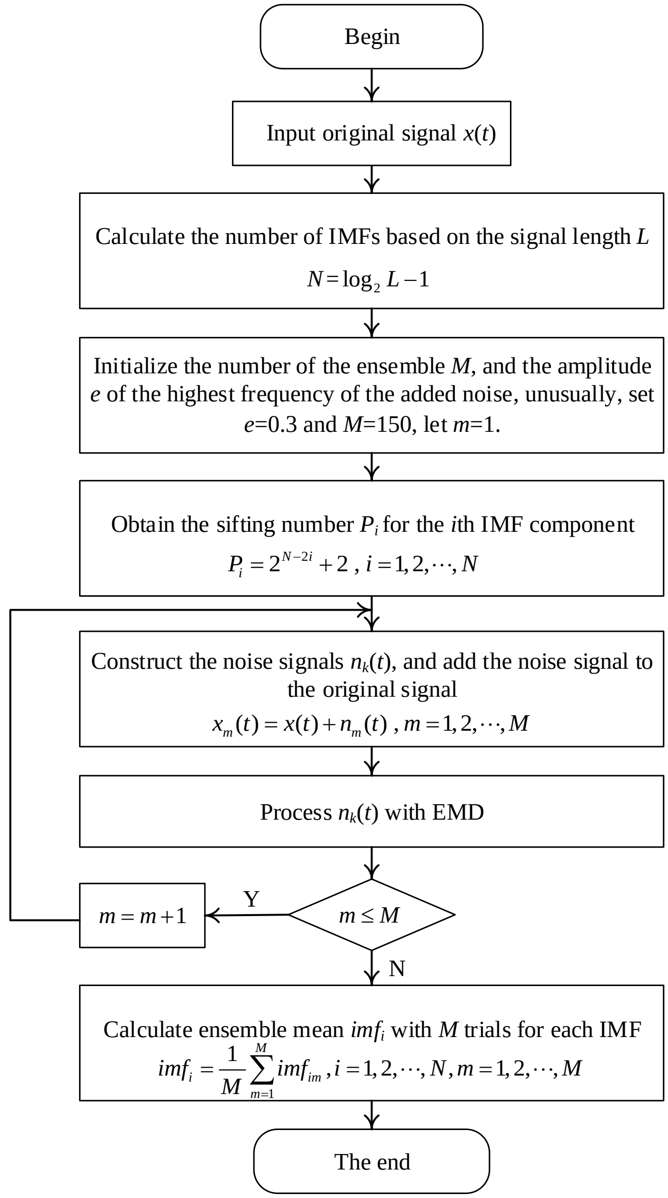

Fig 6. Flow chart of the proposed self-adaptive EEMD method

3.2 Alogrthm simulation

In this section, an experimental signal is processed using the above proposed algorithm to test this algorithm . Some typical signals in locomotive bearing vibration are chosen to make up the simulation signal. As we know, the impact and modulation signals are two kinds of typical signal in locomotive, so the simulation signal consists of impact and modulation signals. Since a train have different speeds in motion, different kinds of frequency sinusoidal signals were used to represent specific rotating frequencies of the locomotive bearing. Therefore, four signals were selected to represent the different physical meanings of the locomotive bearing in the simulated signals. Figure 7 (a)-(e) shows the four components and the simulated signal.

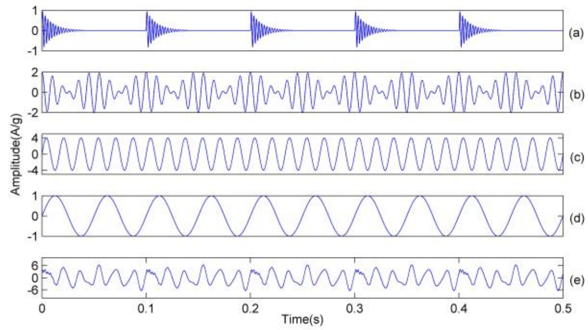

Fig 7. The four components and the simulation signal

First the proposed algorithm is applied to process the simulated signal to identify the effect of the algorithm. The decomposition results of the first four IMFs are shown in Figure 8. Obviously, the figures of IMF 1-4 are respectively corresponding to the impact signal, the modulation, the high-frequency sinusoidal components and the low frequency sinusoidal. Compared the results of the IMFs in Figure 8 with the original signal components in Fig.7 (a)-(d), it could find that different signal components contained in the experimental signal are effectively decomposed by using the proposed algorithm.

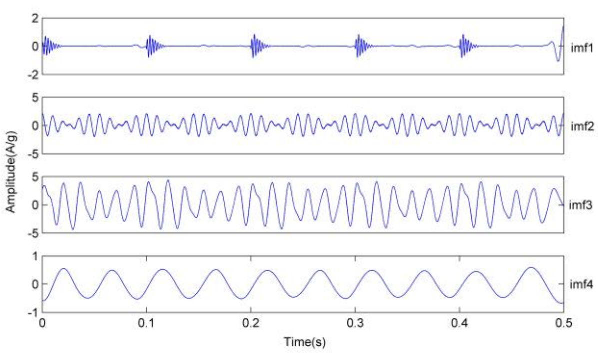

Fig 8. The first four IMFs of the simulation signal processed with self-adaptive EEMD method

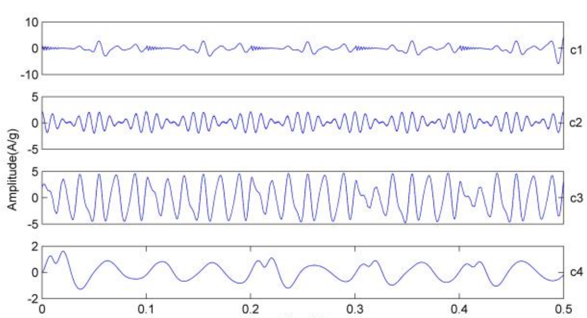

Fig 9. The first four IMFs of the simulation signal processed with original EEMD method

To show the validity of the proposed algorithm, the simulated signal was also processed with added noise, which amplitude was 0.3 and the sifting number was 20. Figure 9 shows the decomposition results of the IMFs. The mode mixing problem still exists in some IMF components and lead to distortions. For instance, the first IMF component includes both impact signal and modulation signal. Moreover, the fourth IMF component is distorted at some maximum points. The results show that the conventional EEMD is unable to decompose the signal accurately.

From the above simulations, it could be concluded that the proposed self-adaptive EEMD algorithm is capable of decomposing signal more accurate than EEMD algorithm. In the process of the decomposition, the amplitude of the added white noise signal change as a sinusoidal function, and the frequency also has a variable sifting number for different IMF components.

4 Application to fault diagnosis of locomotive driving system

In this section, the proposed method is applied to diagnose the early flaw fault occurring in locomotive driving system. The locomotive driving system is one of the major components and also one of the typical rotating machinery used in wheel of bogie. It is of great importance to diagnose the fault of the train wheel as early as possible to avoid the casualties and property losses.

Figure 10 shows the train wheel and the location of the vibration data acquisition device. An accelerometer is installed on the locomotive driving system, which is used to acquire the vibration signals. The schematic model of the wheel bogie is shown in Figure 11. This train wheel consists of a gearbox, a motor, an axle and a pair of wheels. The gearbox connects the motor and the axle.

In this study, two kinds of fault locomotive bearing were tested to evaluate the performance of the self-adaptive EEMD method. A crack at the inner ring and at the outer ring is created respectively to simulate the locomotive bearing faults. Figure 12(a) shows the inner ring fault, and (b) shows the outer ring fault of the locomotive bearing.

The outer race vibration signal and the inner race vibration signal were used in this paper. Each record was digitized at 12 KHz with 16-bit resolution. The experimental locomotive bearing parameters of the gearing are shown in Table 1.

Fig 10. The location of accelerometer

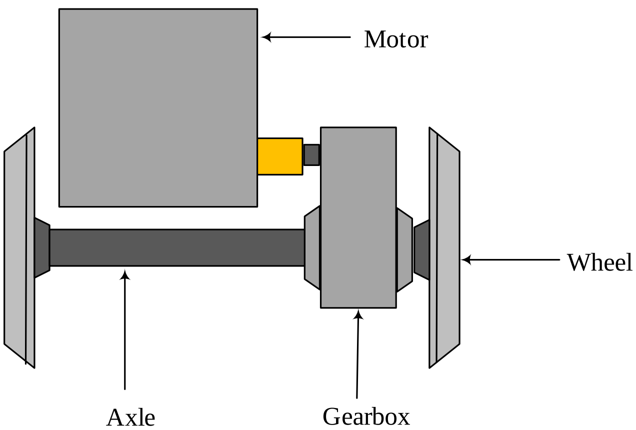

Fig 11. The schematic model of wheel bogie

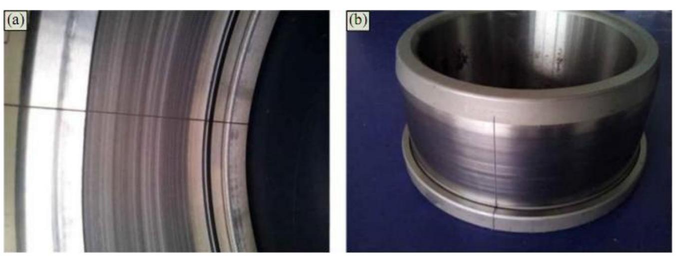

Fig 12. (a) The inner ring fault, (b) the outer ring fault of the locomotive bearing

Table 1. The specifications of the testing locomotive bearing

Type	SKF 6205-2RS
Diameter of the outer race	52mm
Diameter of the inner race	25mm
Pitch diameter (D)	7.49mm
Number of the roller (z)	8
Contact Angle(α)	0

To simulate the fault of the locomotive bearing, an artificial crack with a width of 0.007mm on the surface of out race and a width of 0.21mm on the inner surface were made with a wire-electrode cutting machine. Two sets of data were used to run the test. The acquired vibration signal from the locomotive bearing with the flaw on the outer race is given in Figure 13(a), Figure 13(b) shows its frequency spectrum. Figure 14(a) shows the vibration signal with crack on the inner race, and Figure 14(b) shows its frequency spectrum.

From Figure 13 and Figure 14, we can see that there is a serious of impulses in both of the time-domain waveform. The vibration signal usually contains different kinds of noise, and it is hard to identify the feature of the signal. There is a crack on the bearing in the locomotive driving system, which pass the fixed accelerometer every turn. It can be seen that every time the flaw rotate with the bearing, and there is an impulse in the time-domain waveform which is the mainly components of the vibration collected from. Apart from these impulses, it is hardly to find any useful fault characteristics. This might be due to the fault characteristics of the locomotive driving system are hidden by the background noise and some other normal vibration components.

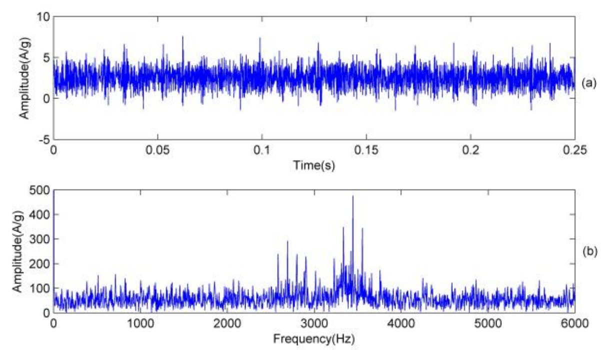

Fig 13. The vibration signal with cracked on outer race (a) time domain waveform (b) frequency spectrum

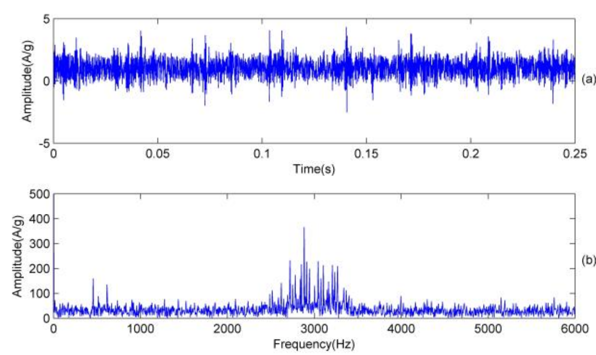

Fig 14. The (a) time domain waveform (b) frequency spectrum

To extract the fault characteristic of the locomotive bearing with cracks, the proposed self-adaptive EEMD is used to process the acquired vibration signals. The first IMF decomposed by the proposed method contains the most abundant information more than all of the other IMFs, and therefore it had been chosen for further study.

The first IMF of the vibration signal with outer race fault is plotted in Figure 15. Figure 15(a) is the result processed using self-adaptive EEMD method and Figure 15(b) is the result processed using EEMD method. From Figure 15(a), there are impulses with the period T_1=0.0095s. Figure 16 shows the IMF results the vibration signal with inner race fault, where Figure 16(a) shows the result decomposed by using self-adaptive EEMD method, and (b) is processed by EEMD method. It is easy to get the impulses with the period T_2= 0.0078s from Figure 16(a).

The parameters of the locomotive bearing in the Table 1 were used to identify the fault type. The ball pass frequency of the outer race (*BPFO*) can be obtained by the following formula.

$$BPFO = \frac{1}{2}(1 - \frac{d}{D_M}\cos\alpha)\, f_n Z \qquad (9)$$

If the surface of the outer race suffers a defect, every time the rolling element passes through the crack and periodic impulses will be created with interval Δt as:

$$\Delta t = \frac{1}{BPFO} \qquad (10)$$

Similarly, the ball pass frequency of the inner race (*BPFI*) is given by:

$$BPFI = \frac{1}{2}(1 + \frac{d}{D_M}\cos\alpha)\, f_n Z \qquad (11)$$

According to the parameters of the test locomotive bearing listed in Table 1 and Equation (9), the outer race characteristic frequency *BPFO* was 101.5Hz and the periodical impact intervalΔt_1 was 0.0099s. It is very close to the calculation (T_1=0.0095s). Calculated by using Equation (11), the inner race characteristic frequency *BFPI* was 138.2Hz and the periodical impact interval Δt_2 was 0.0072s, which is approximate to T_2 (0.0078s). Thus, the proposed self-adaptive EEMD algorithm is capable of extracting the fault characteristics from the normal components effectively.

In order to compare the performance of the proposed algorithm with EEMD, use EEMD to process the same signal. With a sifting number of 20, a white noise with amplitude of 0.2 was used to process the collected vibration signal and the first IMF component is shown in respectively figure. Despite the periodic impulses in the waveform of the IMF, the impulse caused by the crack, the rotation of the bearing and background noise are decomposed into the same IMF, which means the mode mixing problem still exists. In view of the decomposition results, it is inferred that the proposed algorithm has a better performance than the EEMD in the extracting fault characteristics from the locomotive bearing vibration signal.

Although the proposed algorithm shows a better decomposition performance than EEMD in the experiments and application, we cannot absolutely make sure that it is effective for all applications. The self-adaptive EEMD algorithm is proposed based on some simulations and therefore it has its shortcoming. We are still working to figure out a way to improve the integrity and the effectiveness of the proposed algorithm and hopeful the improved result can be achieved and will be shown in near feature.

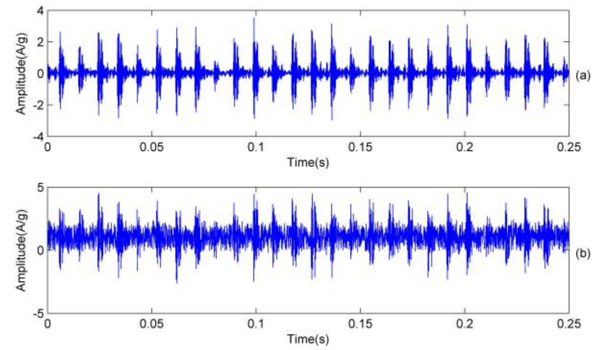

Fig 15. The first IMF with outer race fault extracted by (a) self-adaptive EEMD method, (b) original EEMD method

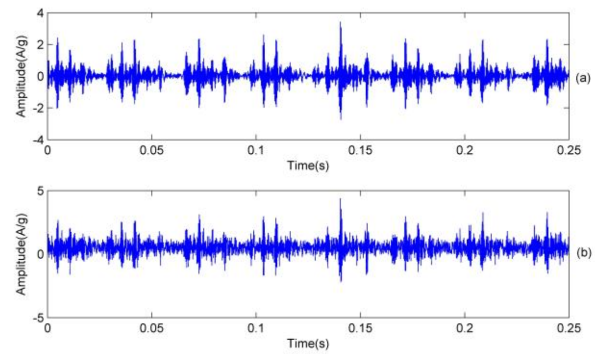

Fig 16. The first IMF with inner race fault extracted by (a) self-adaptive EEMD method, (b) original EEMD method

5 Conclusions

This paper proposed a self-adaptive EEMD algorithm to improve the decomposition performance of the EEMD method in mode mixing for the locomotive driving system in the feature extract and fault diagnosis. Different from the EEMD method with fixed parameters, the amplitude and the sifting number of the added noise are self-adaptively chosen in the process of the decomposition process. Compared the proposed self-adaptive EEMD algorithm with the EEMD method, it is found that the results decomposed by the proposed algorithm is more accurate. Then the proposed algorithm was applied to diagnose an early fault occurring in locomotive driving system. All the results proved that the proposed algorithm has a better performance than the EEMD in the feature extraction and fault diagnosis.

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