

# Blind source extraction based on EMD and temporal correlation for rolling element bearing fault diagnosis

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## Abstract

**Purpose** – Fault diagnosis methods based on blind source separation (BSS) for rolling element bearings are necessary tools to prevent any unexpected accidents. In the field application, the actual signal acquisition is usually hindered by certain restrictions, such as the limited number of signal channels. The purpose of this study is to fulfill the weakness of the existed BSS method.

**Design/methodology/approach** – To deal with this problem, this paper proposes a blind source extraction (BSE) method for bearing fault diagnosis based on empirical mode decomposition (EMD) and temporal correlation. First, a single-channel undetermined BSS problem is transformed into a determined BSS problem using the EMD algorithm. Then, the desired fault signal is extracted from selected intrinsic mode functions with a multi-shift correlation method.

**Findings** – Experimental results prove the extracted fault signal can be easily identified through the envelope spectrum. The application of the proposed method is validated using simulated signals and rolling element bearing signals of the train axle.

**Originality/value** – This paper proposes an underdetermined BSE method based on the EMD and the temporal correlation method for rolling element bearings. A simulated signal and two bearing fault signal from the train rolling element bearings show that the proposed method can well extract the bearing fault signal. Note that the proposed method can extract the periodic fault signal for bearing fault diagnosis. Thus, it should be helpful in the diagnosis of other rotating machinery, such as gears or blades.

**Keywords** Fault diagnosis, Blind source extraction, Signal decomposition, Temporal correlation

**Paper type** Research paper

## 1. Introduction

Rolling element bearings play an important role in industrial manufacturing and rotating machinery, such as gearboxes, train axles and turbines. Their health states tend to degrade due to repeating rotations under harsh working conditions. To ensure the industrial safety



and operation efficiency, a lot of related prognosis and fault diagnosis methods have been developed (Wang *et al.*, 2018; Feng *et al.*, 2013; Zhao *et al.*, 2019).

Fault diagnosis based on the blind source separation (BSS) is one of many interesting branches. Thanks to the valuable work done by Gelle *et al.* (2001, 2003), BSS began to attract more and more attention in the condition monitoring and fault diagnosis (Sadhu *et al.*, 2017). One important precondition for the traditional BSS fault diagnosis is the signal acquisition. Multiple source signals from different monitoring locations need to be input to identify the potential fault. However, the installment of multiple sensors are usually unfeasible owing to certain industrial circumstance (Hong and Liang, 2007). Normally, a single channel of vibration signal is usually obtained to assess the health condition. Therefore, it is necessary to investigate the BSS fault diagnosis with single channel of vibration signal, known as the underdetermined BSS fault diagnosis. Related research can be divided into two categories (Li *et al.*, 2019). The first one is to create the separation through an estimation of the mixed matrix between the source and the observed signal. The underdetermined BSS problem can be converted into a transform domain as a problem of mixed matrix estimation, known as sparse component analysis (SCA). The other is to transform the underdetermined method into a positive definition problem through the signal decomposition method.

For the research on the SCA, time–frequency transform methods, such as short-time Fourier transform (He *et al.*, 2018), wavelet transform (Yang and Nagarajaiah, 2014), are adopted to transform the observed signals into the time–frequency domain to obtain the sparse signal representations. Then, the estimation of the mixed matrix is carried out in the time–frequency domain. Typically, clustering algorithms, such as fuzzy C-means clustering (He *et al.*, 2018; Hu *et al.*, 2016), K-hyperline clustering (Qin *et al.*, 2015) and density peaks clustering (Lu *et al.*, 2019) are used to obtain the mixed matrix. Then, the source signal is usually recovered by minimizing the  $L_1$  norm. However, the compound signal in the frequency domain or other low-dimension space is often not sparse enough, because of complex influence factors such as the nature of the equipment, the vibration caused by equipment malfunction, the interaction among the accessories and the noise of the surrounding environment (Zibulevsky and Pearlmutter, 2001; Bofill and Zibulevsky, 2020).

For the research based on the signal decomposition, signal decomposition methods, such as wavelet decomposition (Hong and Liang, 2007; Zuo *et al.*, 2005), empirical mode decomposition (EMD) (Li *et al.*, 2013; Wang *et al.*, 2014a) and variational mode decomposition (Tang *et al.*, 2016) are firstly used to obtain multi-signal components. Then, the desired signal sources are estimated through independent component analysis (ICA) (Li *et al.*, 2013; Wang *et al.*, 2014b). ICA is based on the assumption that the desired components are statistically independent. And, it is assumed that the independent component must have non-Gaussian distributions. However, a large number of signals in engineering practice do not always satisfy all of the assumptions, especially the statistical independence assumption. In addition, as both source signal and mixing matrix are unknown, the order of the independent components cannot be determined, which is known as permutation ambiguity (Hyvärinen *et al.*, 2004). As only one or some desired signals are required for the fault diagnosis, the blind source extraction (BSE) is more suitable. To address the above-mentioned problems, Barros and Cichocki (Barros and Cichocki, 2001) proposed to extract certain signal component with a temporal structure. The desired signal component can be extracted given prior correlation function information. It is a relief of the computation burden because only critical signal components are extracted. Zhang and Zhang (Zhang and Yi, 2006a) further improved this temporal structure method by proposing a multi-shift temporal correlation method. Inspired by their work, this paper provides a BSE method

based on the EMD algorithm and the multi-shift temporal correlation for bearing fault diagnosis.

The rest of this paper is outlined as follows. In Section 2, the fundamentals of EMD and the temporal correlation method are reviewed. In Section 3, the underdetermined BSE method for rolling element bearing fault diagnosis is proposed. In Section 4, simulated and real bearing fault signals, including a vibration data set, acquired from industrial train axle bearings are used to verify the effectiveness of the proposed method. Conclusions are drawn in the final section.

## 2. Fundamentals of empirical mode decomposition and temporal correlation method

### 2.1 Temporal correlation method for blind source extraction

BSE is a simpler and faster technique developed based on the BSS. Denote the source matrix  $s(t)$  is composed of  $n$  source signal vectors as  $s(t) = [s_1(t), \dots, s_n(t)]$  and the observed signal matrix as  $x(t) = [x_1(t), \dots, x_k(t)]$ . Assume the source matrix  $s(t)$  is linearly mixed by an unknown matrix  $A$  describing the linear combination of the  $s(t)$  is a full rank  $k \times n$  matrix. Thus, the mixture can be written as [equation \(1\)](#):

$$x(t) = A*s(t) + N(t) \quad (1)$$

where  $A$  is the mixing matrix, and  $N(t)$  is Gaussian noise. And, the separation process is regarded as underdetermined BSS when  $k$  is less than  $n$ .

BSS methods usually separate those source vectors simultaneously, accompanying some problems such as the permutation ambiguity and computation burden ([Hyvärinen et al., 2004](#)). BSE is more attractive when a particular signal component or a specified order of separation of the signal sources is desired. Many source extraction algorithms extract a desired signal as the first output given *a priori* information, such as sparseness ([Zibulevsky and Zeevi, 2002](#)) and high-order statistics ([Zhang and Yi, 2006b](#)).

Assume that the desired signal  $s_i$  is temporally correlated, and they have different autocorrelation functions. Namely, the source signal satisfies the following conditions for a specific time delay  $\tau$ :

$$\begin{cases} E[s_i(t)s_i(t - \tau)] \neq 0 \\ E[s_j(t)s_j(t - \tau)] = 0 \quad \forall j \neq i \end{cases} \quad (2)$$

where  $E$  stands for the ensemble average operator.  $t$  is the time index and  $\tau$  is the time delay.

To obtain the desired signal, the correlation function between the output signal  $y(t)$  and its time-delayed version have to be maximized. Thus, the objective function is shown as [equation \(3\)](#). The extracted signal  $y(t)$  can be obtained by  $y(t) = \omega^T *_{\varepsilon} x(t)$ , and  $\omega$  is the extractor vector. To avoid the scaling problem, the objective function is under the constraint  $\|\omega\| = 1$  ([Barros and Cichocki, 2001](#)):

$$J(\omega) = \sum_{i=1}^P E[y(t)y(t - \tau)] = \omega^T E[x(t)x(t - \tau)^T] \omega \quad (3)$$

where  $y(t)$  is the output signal and  $y(t) = \omega^T x(t)$ .

Zhang and Zhang (Zhang and Yi, 2006a) further conducted this objective function to multi-shift form and obtain the desired de-mixing matrix through a fixed point algorithm (Zhang and Yi, 2006a). This algorithm is found to be faster and more robust compared to previous versions. The objective function and the desired extraction vector are shown as equation (4):

$$J(w) = \sum_{i=1}^P E[y(t)y(t-i\tau)] = w^T \left( \sum_{i=1}^P E[x(t)x(t-i\tau)] \right) w \quad (4)$$

The new objective function extended the temporal correlation to multi-shift form.  $P$  is a constant value usually set between three to five. Increasing the shift increases the number of sequential correlated components, which will involve more information for signal extraction. According to the fixed point algorithm, the learning rule stated in equation (13) accepts the eigenvector of  $x(t)x(t-\tau)$  as a fixed point corresponding to the maximum eigenvalue. Thus, the extraction vector can be obtained through equation (5):

$$\begin{cases} R_x(\tau) = E[x(t)x(t-\tau)] \\ w = \text{EIG} \left( \sum_{i=1}^P (R_x(i\tau) + R_x(i\tau)^T) \right) \end{cases} \quad (5)$$

where  $\text{EIG}(t)$  is the operator that calculates the normalized eigenvector corresponding to the maximal eigenvalue of the real symmetric matrix  $T$ .

### 2.2 Empirical mode decomposition algorithm

The EMD algorithm was developed by Huang *et al.* (1998) and can decompose a signal into multiple components, named intrinsic mode functions (IMFs). An IMF is a function that satisfies the following two conditions. The first one is that the number of extrema and the number of zero crossings must either equal or differ at most by one in the whole data set. The second one is that the mean value of the envelope defined by local maxima, and the envelope defined by the local minima is zero at any point. Each IMF indicates a simple oscillatory mode imbedded in the signal. The EMD algorithm contains the following steps (Gao *et al.*, 2008; Lei *et al.*, 2013).

- Identify all the local maxima and minima of the signal, and interpolate the local maxima and the minima by cubic spline lines to form upper and lower envelopes.
- Calculate the mean  $m_1$  of the upper and lower envelopes, and calculate the difference between the signal  $x(t)$  and  $m_1$  as the first component  $h_1$ .

$$x(t) - m_1 = h_1 \quad (6)$$

If  $h_1$  is an IMF, set it as the first IMF of  $x(t)$ . If  $h_1$  is not an IMF, take it as the original signal and repeat the above steps, then:

$$h_1 - m_{11} = h_{11} \quad (7)$$

After  $d$  times iterations,  $h_{1k}$  becomes an IMF, that is:

$$h_{1(k-1)} - m_{1k} = h_{1k} \quad (8)$$

Set  $h_{1k}$  as  $c_1$ ; thus:

$$c_1 = h_{1k} \quad (9)$$

- Separate the first IMF  $c_1$  from  $x(t)$  by:

$$x(t) - c_1 = r_1 \quad (10)$$

- Take the residue as the original signal and carry out the same process as above, so that other IMFs,  $c_2, c_3, \dots, c_p$  can be obtained, which satisfy:

$$r_{p-1} - c_p = r_p \quad (11)$$

The decomposition process can be stopped when  $r_p$  becomes a monotonic function from which no more IMFs can be extracted.

- The original signal can be represented by summing up all the IMFs and the residue:

$$x(t) = \sum_{i=1}^p c_i(t) + r_p(t) \quad (12)$$

Those obtained IMFs  $c_2, c_3, \dots, c_p$ , contain the signal information of different frequency bands ranging from high to low.

### 3. Proposed algorithm

Combining the above two mentioned methods, this paper proposes a BSE method based on EMD and temporal correlation for bearing fault diagnosis. With the help of the EMD, the single-channel signal can be divided into multiple components. Each component contains different frequency band information, which can be used for fault signal extraction. Thus, the undetermined BSE problem can be transferred into a determined blind extraction problem. After selecting suitable IMFs, the desired fault signal can be extracted.

It should be noted that the input IMFs are crucial to the implementation of the BSE. The input IMFs should contain most of the useful information. To ensure that input IMFs contain the most information of the original signal, the cumulative variance contribution rate of the average eigenvalues (Zhao *et al.*, 2020) is applied in this paper. Input IMFs are selected according to the contribution rate among all the IMF components. First, the multi-channel signal  $x_{new}$  is constructed by combining the original signal and decomposed IMFs. Then, the covariance of the constructed based on the multi-channel signal by  $R_x = (x(t)x(t)^T)$ . Then,  $m$  eigenvalues of variance matrix from  $m$  different frequency components  $\lambda_1, \dots, \lambda_m$  are obtained. Arrange those eigenvalues in descending order, and the variance contribution rate  $C_j$  of a certain frequency component is calculated as [equation \(13\)](#):

$$C_j = \lambda_j / \sum_{i=1}^m \lambda_i \quad (13)$$

Thus, the cumulative variance contribution of the  $q$  frequency components or IMFs can be obtained by [equation \(14\)](#), and the cumulative variance need to be larger than the setting

threshold. The contribution rate threshold is set manually. In this paper, the experience threshold is set as 85%:

$$\sum_{j=1}^q C_j = \sum_{j=1}^q \lambda_j / \sum_{i=1}^m \lambda_i \quad (14)$$

Thus, the number of the input IMFs can be determined and specific steps of the proposed method are as follows:

- Step 1. Denote the input signal  $x[l]$  with signal length  $l$ .
- Step 2. Decompose the input signal into multiple components with the EMD algorithm.
- Step 3. Determine the input IMFs for BSE according to the cumulative variance contribution rate of different frequency components based on the setting threshold.
- Step 4. To eliminate the influence of the direct current (DC) component and correlation among different features, the obtained IMFs are processed through a centralization method to remove the mean value, and then the signal is processed by a whitening treatment method based on principal component analysis (Zhao *et al.*, 2020) shown by equation (15):

$$Z = WX \quad (15)$$

where  $W$  is the whitening matrix,  $X$  is the observed signal matrix and  $Z$  is the whitened signal matrix.

- Step 5. Determine the time delay and extract the desired fault signal using temporal correlation.

The time delay parameter reflects the periodicity of the bearing fault signal. It can be obtained by dividing the sampling frequency by fault frequency.

- Step 6. Obtain the envelope spectrum of the extracted fault signal and identify the fault type.

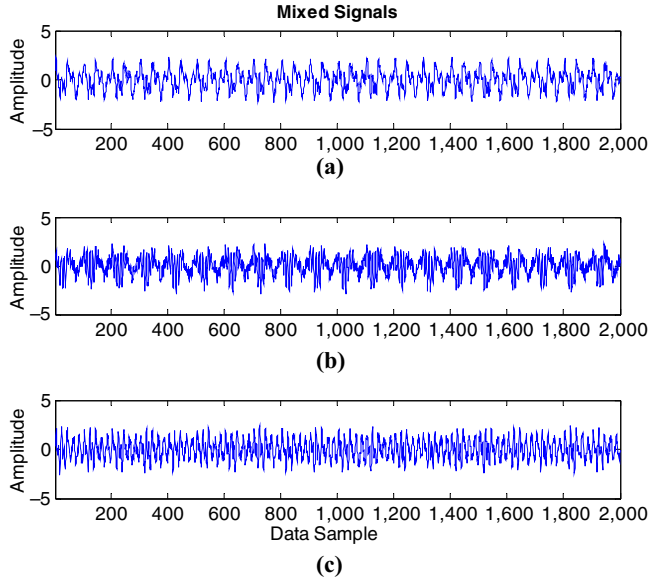
## 4. Experimental validation

### 4.1 Simulated signal validation

To validate the effectiveness of the proposed method, the fault diagnosis is firstly conducted on a simulated bearing fault signal (He *et al.*, 2018). The simulated signal is composed of three signal sources shown as equation (16). The sampling frequency is set as 1,000 Hz:

$$\begin{aligned} s_1(t) &= \cos(2\pi f_1 t + 10) \\ s_2(t) &= 0.5 \cos(2\pi f_2 t + 10) \\ s_3(t) &= \sin(2\pi f_3 t) * [1 + \alpha \sin(2\pi f_4 t)] \end{aligned} \quad (16)$$

where  $f_1 = 20 \text{ Hz}$ ,  $f_2 = 50 \text{ Hz}$ ,  $f_3 = 100 \text{ Hz}$ ,  $f_4 = 10 \text{ Hz}$ ,  $\alpha = 1.6$ . The simulated bearing fault signal is modulated, represented as  $s_3(t)$ . According to equation (1), three source signals are mixed, and the three observed signals are shown as Figure 1.



**Figure 1.**  
Mixed signal

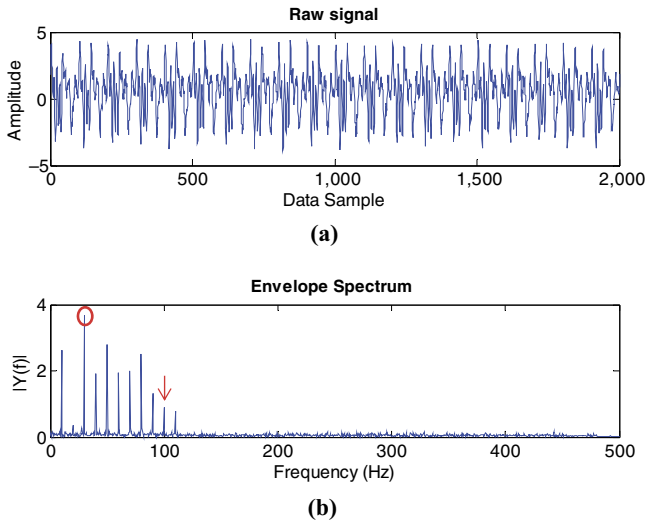
Suppose that only one signal channel can be obtained in the fault diagnosis. The signal in [Figure 1\(a\)](#) is selected as the observed signal. Then, the envelope analysis is applied to analyze this signal, and the envelope spectrum is shown in [Figure 2](#). The harmonic component whose frequency is 20 Hz is more obvious in the frequency spectrum, marked with a red circle. However, the fault frequency is buried by other frequency components, marked with the red arrow. It can be concluded that the envelope analysis is unable to tell the bearing fault frequency from other frequency components.

Thus, the proposed method is used to analyze the same signal. With the specific steps of Section 3, the signal is firstly decomposed into multiple IMFs with EMD algorithm. Then three IMFs satisfying the setting threshold condition are selected, shown as [Figure 3](#).

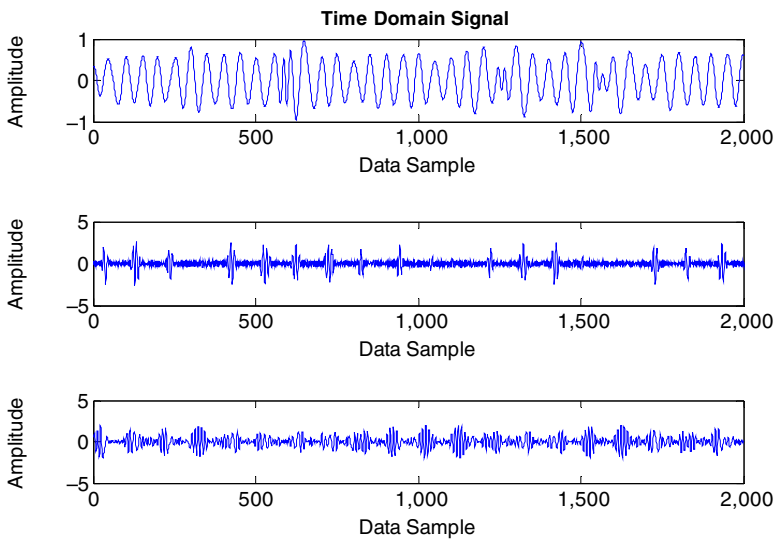
The sampling frequency is 1,000 Hz and the fault frequency is 100 Hz; thus, the time delay is set to 10 according to the proposed method. Thus, the fault signal can be extracted through the temporal correlation method. The extracted signal and its corresponding frequency spectrum is displayed in [Figure 4](#). It can be seen from the figure that the fault signal is well extracted, and the frequency spectrum is much clearer than that in [Figure 2](#).

#### *4.2 Train rolling bearing signal validation*

In this case study, industrial railway axle bearing fault data are used for further comparison experiments. Our experimental platform for collecting railway axle bearing fault data is shown in [Figure 5](#). Through a transmission set, a variable speed DC motor with a speed up to 1,480 r/min is used to drive the rotation of an axle at different speeds. Axle bearings are assembled to the ends of the axle. A lateral load set and a vertical load set are installed to impose practical loads during rail vehicle operation. Fan motors are installed to simulate the effect of natural wind on the opposite of vehicle's running direction. Sensors were mounted on 12 o'clock (directly in the vertical load zone) and 3 o'clock (orthogonal to the vertical load zone) of the bearing casing to acquire vibration data. Two fault bearings were selected from the railway maintenance center and their degradation conditions are shown as [Figure 5\(b\)](#)



**Figure 2.**  
Time domain signal  
and its corresponding  
envelope spectrum

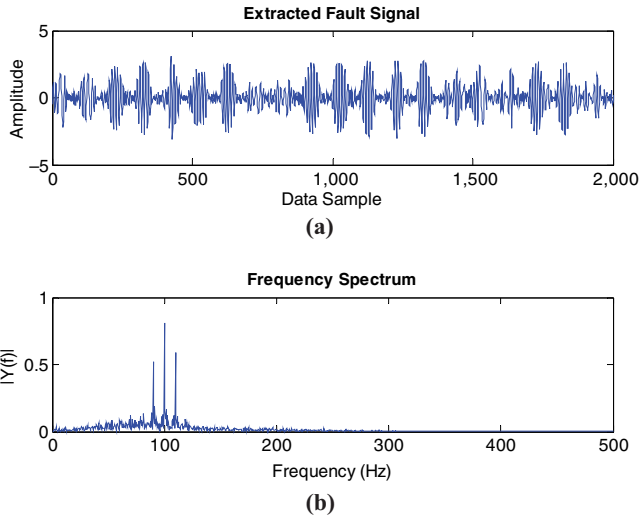


**Figure 3.**  
Selected IMF's based  
on the setting  
threshold for  
simulated signal

and Figure 5 (c), respectively. The sampling frequency is set to 5,120 Hz. The simulated speed and vertical load are set to 65 km/h and 272 kN, respectively. The lateral load is 20 kN. According to the transmission ratio of our experimental platform, an inner race fault frequency and an outer race fault frequency are calculated as 80 and 61 Hz, respectively.

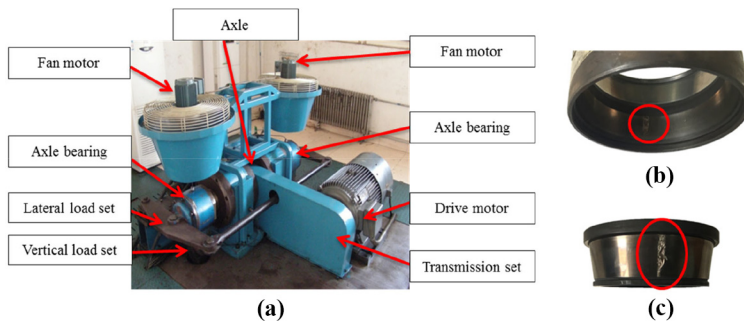
The raw signal of the outer race fault is shown in Figure 6(a). The corresponding envelope spectrum of the raw signal is shown in Figure 6(b). It can be seen that envelope spectrum analysis does not perform well when identifying the outer race fault. No obvious frequency peaks can be found in the spectrum.





**Figure 4.**  
Extracted fault signal  
and its frequency  
spectrum

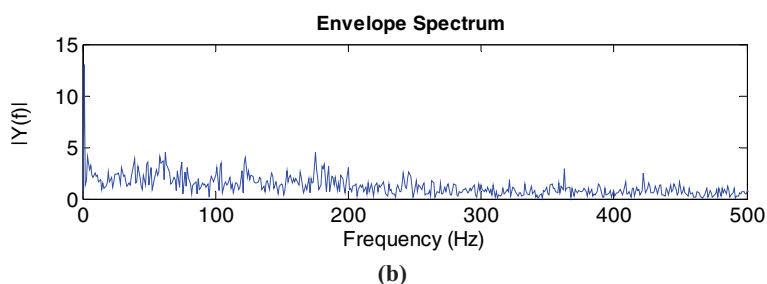
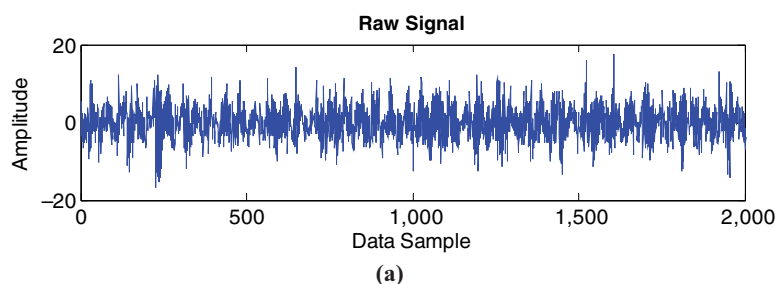
**Figure 5.**  
A designed  
experimental  
platform and  
industrial railway  
axle bearing faults:  
(a) the designed  
experimental  
platform;  
(b) the outer  
race fault;  
(c) the inner  
race fault



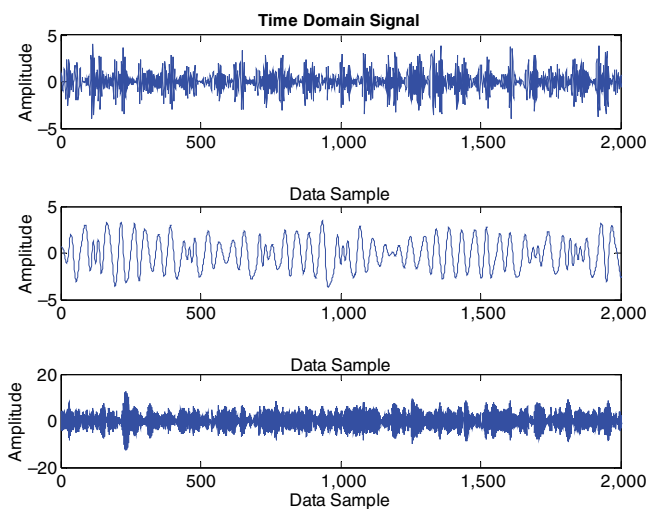
With the proposed method, the same fault signal is analyzed. The number of the chosen IMFs is 3 based on the contribution rate. Selected IMFs are shown in Figure 7. The fault signal is further extracted with those IMFs. According to the time delay calculation method, the time delay is set as 84. The extracted outer race fault signal and its corresponding fault frequency is shown in Figure 8. Figure 8(a) shows that the extracted fault signal displays more obvious periodic components. The corresponding envelope spectrum shows that the fault frequency and its harmonic frequency can be well identified, in which marked with red arrows.

The inner race fault is further analyzed. The raw signal of the inner race fault and its corresponding envelope spectrum is shown in Figure 9. It can be seen from the Figure 9(b) that only the first fault harmonic can be identified through the envelope analysis. Other frequency harmonics are hidden in the background noise.

Again, the proposed method is applied to analyze the inner race fault signal. The selected IMFs are shown in the Figure 10. The time delay parameter is set as 64. The extracted inner race fault signal is shown in Figure 11. The extracted inner race fault signal also shows



**Figure 6.** Envelope analysis of the outer race fault signal: (a) the raw signal of time domain fault; (b) corresponding envelope spectrum of outer race fault signal

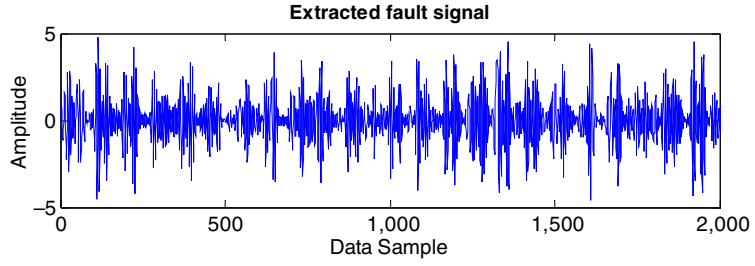


**Figure 7.** Selected IMFs based on the setting threshold for outer race fault

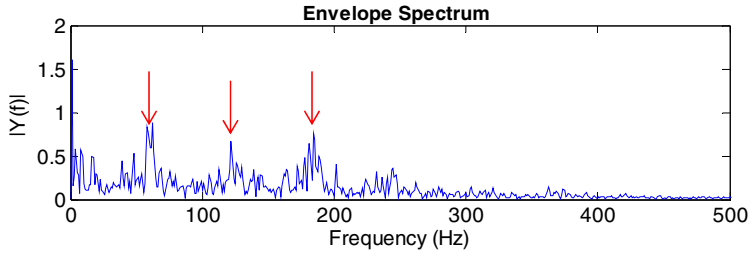
more obvious periodic components. Figure 11(b) shows that two more fault harmonics can be identified compared to the direct analysis with envelope analysis.

## 5. Conclusion

This paper proposes an underdetermined BSE method based on the EMD and the temporal correlation method for rolling element bearings. A simulated signal and two bearing fault signal from the train rolling element bearings show that the proposed method can well

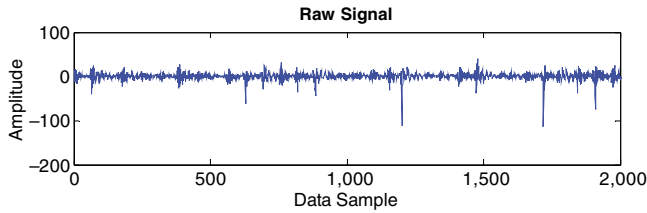


(a)

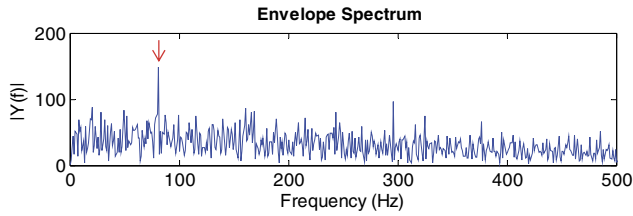


(b)

**Figure 8.** Analysis with the proposed method: (a) extracted fault signal; (b) corresponding envelope of the extracted fault signal



(a)

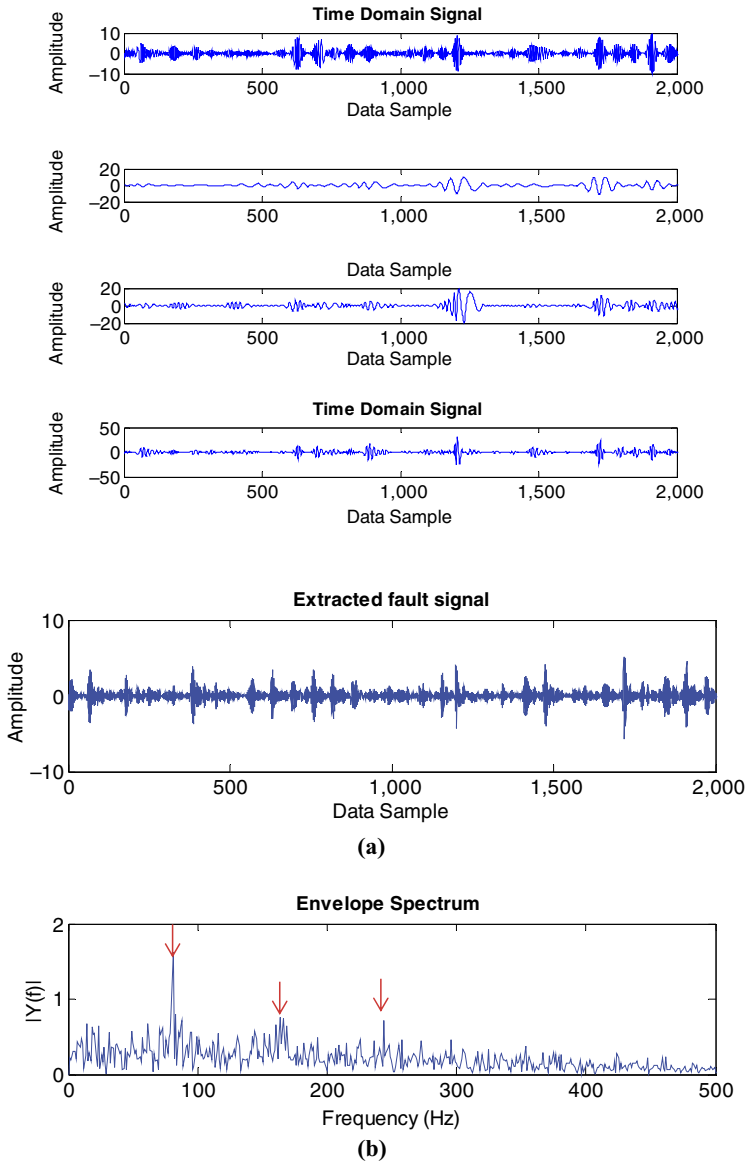


(b)

**Figure 9.** Envelope analysis of the inner race fault signal: (a) the raw signal of time domain fault; (b) corresponding envelope spectrum of the inner race fault signal

extract the bearing fault signal. Note that the proposed method can extract the periodic fault signal for bearing fault diagnosis. Thus, it should be helpful in the diagnosis of other rotating machinery, such as gears or blades.

Further research mainly focus on extending the correlation measure to kernel space. As the EMD algorithm may have the mode mixing problem, the temporal correlation method in kernel space may have a better performance in that case.



**Figure 10.** Selected IMFs based on the setting threshold for inner race fault

**Figure 11.** Extracted fault signal and its envelope spectrum

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