

PAPER • OPEN ACCESS

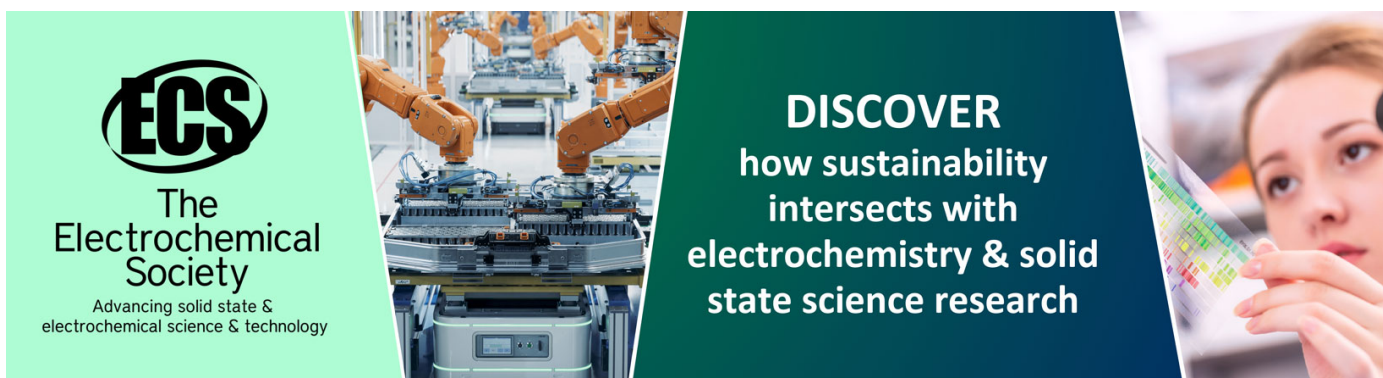
A new fault detection strategy using the enhancement ensemble empirical mode decomposition

To cite this article: Jiawei Xiang and Yongteng Zhong 2017 *J. Phys.: Conf. Ser.* **842** 012002

View the [article online](#) for updates and enhancements.

You may also like

- [Therapeutic effects of *in-vivo* radiodynamic therapy \(RDT\) for lung cancer treatment: a combination of 15MV photons and 5-aminolevulinic acid \(5-ALA\)](#)
Dae-Myoung Yang, Dusica Cvetkovic, Lili Chen et al.
- [Copper Fill of Microvia Using a Thiol-Modified Cu Seed Layer and Various Levelers](#)
Wei-Ping Dow, Chih-Chan Li, Meng-Wen Lin et al.
- [RDT accuracy based on age group in hypoendemic malaria](#)
L Siahaan, M Panggabean and Y C Panggabean



ECS
The
Electrochemical
Society
Advancing solid state &
electrochemical science & technology

DISCOVER
how sustainability
intersects with
electrochemistry & solid
state science research

A new fault detection strategy using the enhancement ensemble empirical mode decomposition

Jiawei Xiang *, Yongteng Zhong

College of Mechanical and Electrical Engineering, Wenzhou University, Wenzhou, P.R.China

E-mail: wxw8627@163.com; zhongyongteng@wzu.edu.cn

* wxw8627@163.com. (Jiawei Xiang)

Abstract. The vibration signals of mechanical components are non-linear and non-stationary and the feature frequencies of faulty bearings will be difficult extracted. This paper presents a new approach that combines the ensemble empirical mode decomposition (EEMD), the random decrement technique (RDT), and envelope spectrum for the fast detection of faults in bearings. The proposed approach uses the optimized and fast EEMD algorithm to extract intrinsic mode functions (IMFs) from vibration signals able to tack the feature frequency of bearings. If the Impulse response signal of the first IMF is unclear, it is further extracted by the RDT, and the feature frequencies are determined by analyzing the signals using envelope spectrum. The advantages of this method are its computational efficiency, and the strong non-stationary vibration signal decomposition and impulse signal extraction abilities. Numerical simulations and experimental data collected from faulty bearings are used to validate the proposed approach. The results show that the use of the EEMD, the RDT, and the envelope spectrum is a suitable and fast on-line strategy to detect faults of mechanical components.

1. Introduction

Damage detection using vibration signals and the corresponding structural health monitoring techniques are the important topic in scientific world [1-7]. Rolling element bearings are the two key components in mechanical systems. The failure of these components (e.g., bearings) will result in the deterioration of machine operating conditions. Therefore, it is important to timely detect faults in bearings. Owing to vibration signals carry a great deal of information representing mechanical equipment health conditions, the use of vibration signals is quite common in the field of condition monitoring and diagnostics of mechanical systems [8-16]. Fault features (the impact pulse amplitude modulation is caused by the defects moving in and out of the loading zone) can be extracted from the vibration signals with signal processing techniques, such as the combinations of wavelet transform and independent component analysis (ICA) [8], the customized lifting multiwavelet packet information entropy [9], the development of an adaptive ensemble empirical mode decomposition EEMD method [10], spectral kurtosis (SK) in associate with the fast computation of the kurtogram technique [11,12], the joint integral and wavelet transform approach [13], the hybrid of PPCA and spectral kurtosis (SK) technique [14], the manifold subspace distance method [15], and the Teager energy operator (TEO) based parameter-free and broadband approach [16], etc.



For the fault detection in bearings, it is expected that a desired time–frequency analysis method has good computational efficiency and resolution in both time and frequency domains. Recently, EMD has been developed and widely applied in fault diagnosis of mechanical systems. EMD is a way to decompose a signal into IMFs along with a trend, and obtain instantaneous frequency signals (approximate stationary signals). Therefore, it is designed to work well for a signal that is non-stationary and nonlinear. Therefore, EMD is a time–frequency analysis technique, which can decompose the complicated signal (non-stationary signal) into a set of complete and almost orthogonal components (stationary signals) named intrinsic mode functions (IMFs) [17]. To reduce mode mixing, Wu and Huang proposed a new ensemble EMD (EEMD) method [18]. EEMD is a noise-assisted data analysis method by adding finite white noise to excite the original signals, which can eliminate the mode mixing phenomena. In practical applications, the key issues are how to properly select the added noise amplitude (affects EEMD decomposition results). If the added noise amplitude is inappropriate, it will cause a large amount of residual noise. To overcome this problem, Yeh et al. [19] presented the complementary of the use of EEMD method and applied it to detect simulation signals with a good performance. Recently, Wang et al. [20] proposed an optimized EMD/ EEMD algorithm to speed up the computational efficiency to one thousand times. They also proved that the computational complexity of the EMD is equivalent to fast Fourier transform (FFT). Hence, the optimized EEMD method might be a good choice to be applied to on-line detect faults in mechanical systems.

The fundamental concept of the RDT [21] is that the random response of a structure (stationary signal) can be separated into two parts, i.e., a deterministic part and a random part. By averaging enough sample responses, the random part will be enormously decreased. Ibrahim verified that the deterministic part that remains is the free-decay response (impulse response signal) associated with the initial condition in time domain [22-23]. Hence the main advantage of RDT is the strong ability to extract impulse response signals from noisy conditions. In summary, EMD/EEMD can decompose complicated non-stationary signal into a collection of stationary IMFs, whereas RDT is suitable to process stationary signals. Therefore, it might be agreeable to combine them into a hybrid one.

2. A brief review of EEMD and RDT

In 1998, Huang et al. introduced the EMD, which is able to decompose complicated signal into a collection of stationary IMFs [17]. Therefore, it has been often used in non-stationary signal processing [20]. In the EMD method, the data $x(t)$ is decomposed in terms of IMFs c_j as [17]

$$x(t) = \sum_{j=1}^n c_j + r_n \quad (1)$$

where r_n is the residual of data $x(t)$, after n number of IMFs are extracted.

However, mode mixing appears to be the most significant drawback of EMD [19]. Therefore, in 2009, a new artificial noise-excited EMD method was proposed by Wu and Huang, which called EEMD [20]. The procedures are similar to EMD except only one groups of white noise with finite amplitude are added into the original signals and the procedures are summarized as follows:

(1) Add a white noise $n_i(t)$ series (noise level is N_i) to the targeted data and decompose the data with added white noise into IMFs as

$$x(t) + n_i(t) = \sum_{j=1}^n c_j^i(t) + r_n^i(t) \quad (2)$$

where $i = 1, 2, \dots, q$ and q is the average times (ensemble number).

(2) Repeat step1 q times with different white noise series $n_i(t)$.

(3) Obtain the (ensemble) means of corresponding IMFs of the decompositions as the final result, that is

$$x(t) + n_i(t) = \frac{1}{q} \sum_{i=1}^q \sum_{j=1}^n c_j^i(t) + \frac{1}{q} \sum_{i=1}^q r_n^i(t) = \sum_{j=1}^n d_j(t) + r_n(t) \quad (3)$$

where $d_j(t)$ is the j th IMFs of EEMD decomposition as

$$d_j(t) = \frac{1}{q} \sum_{i=1}^q c_j^i(t) \quad (4)$$

and $r_n(t)$ is the final residual of EEMD decomposition as

$$r_n(t) = \frac{1}{q} \sum_{i=1}^q r_n^i(t) \quad (5)$$

The fast algorithm of EMD/EEMD is proposed by Wang et al. in Ref. [20], which will speed up the computational efficiency to one thousand times than that of traditional EMD/EEMD. The computational complexity of the EMD/EEMD is proved to be equivalent to FFT. Therefore, the EEMD method can be employed to quickly detect faults in mechanical components.

RDT can be used to describe the free decay response of the system (in the present, it refers to the impulse response signal). The advantage of this technique is that one obtains the free response from the stationary random response of the system [22-23]. In this regard, the response signal is divided into a number of segments L , each of length τ . All of these segments should have the same initial condition (triggering value), i.e., $x_i(t_i) = x_s = \text{const.}$, $i = 1, 2, \dots, L$. A threshold level should be selected to obtain L segments. The ensemble average of the L segments yields the random decrement, which can be mathematically expressed by

$$x(\tau) = \frac{1}{L} \sum_{i=1}^L x_i(t_i + \tau) \quad (6)$$

where $x_i(t_i) = x_s$ for $i = 1, 2, \dots, L$.

It points that the RDT requires no knowledge of the excitation as long as it is stationary, zero-mean Gaussian random process [22-23].

3. The diagnosis method using EEMD, RDT and Hilbert envelope spectrum

Fig.1 shows the flowchart of the present diagnosis method using EEMD, RDT and Hilbert envelope spectrum. Three steps in the proposed approach are:

- (1) Obtain the first IMF of raw signal using EEMD

In order to overcome the drawback of careful selection of an IMF using EEMD method, we fix the first IMF in the present approach, and the performance will be verified using numerical simulations and experimental investigations. Moreover, for the mechanical systems, especially the bearing or gear with faults, the high frequency modulation signals is always located in the IMF1.

- (2) Perform Hilbert envelope spectrum analysis and obtain the detect result

For the IMF1 or the impulse response signal, Hilbert envelope spectrum analysis is applied and the demodulation frequency is finally obtained. Compared the demodulation frequency with the theoretical fault feature frequency, the type of bearing and gear fault can be determined. If the impulse response signal of the first IMF (IMF1) is clearly revealed, we will obtain the detect result using only Hilbert envelope spectrum analysis. Otherwise, RDT is further applied to extract the purified impulse response signal.

- (3) Extract impulse signals from the IMF1 using RDT

In the present, RDT is applied to extract the impulse response signal of faulty bearings and gears from the stationary signal in IMF1. Then we go back to step 2 and repeat perform Hilbert envelope spectrum analysis and finally obtain the detect result.

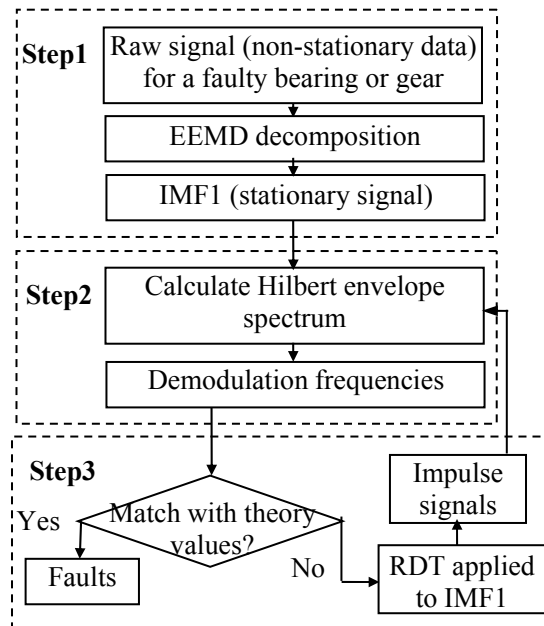


Fig. 1. The flowchart of fault detection approach

4. Numerical simulation

To simulate the bearing faults, we use an artificial simulation signal in this section. The low frequency steady state signal, high frequency transient signal and the noise are included, and the simulation signal is defined as

$$x(t) = s(t + T) + c(t) + e(t) \quad (7)$$

where $s(t)$ is the impulse response signal (simulate fault induced vibration of bearing), T is the impulse period (feature frequency), $c(t)$ is the low frequency steady state signal relative with the rotating frequency and its harmonic components, and $e(t)$ is the noise (normally distributed pseudorandom numbers).

In Eq.(7), $c(t)$ and $s(t)$ are given by

$$c(t) = 0.5 \sin(2\pi f_0 t) + 0.15 \sin(4\pi f_0 t) + 0.05 \sin(6\pi f_0 t) \quad (8)$$

and

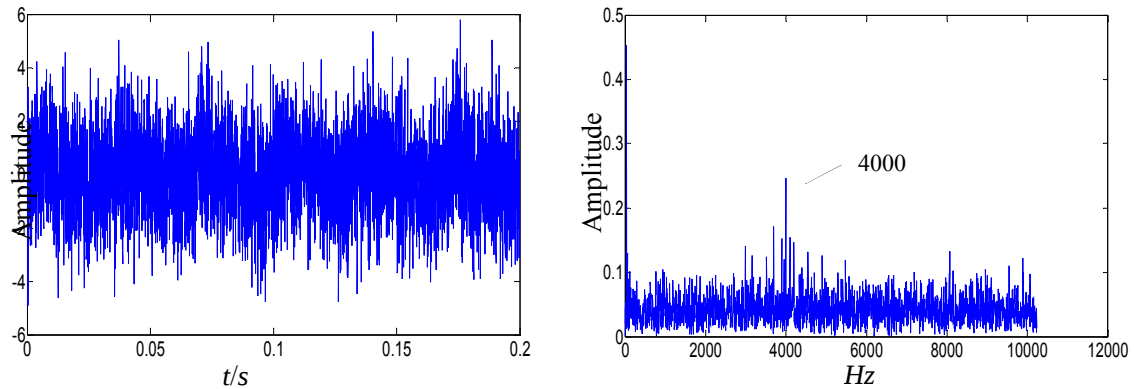
$$s(t) = e^{-Bt} \cos(2\pi f_n t) \quad (9)$$

in which f_0 is the fundamental frequency of the low frequency steady state signal, f_n is the natural frequency. $B = 2\pi f_n \xi$ is the attenuation coefficient depended on damping ratio ξ and natural frequency f_n . Suppose the parameters are: $T = 0.01s$ (the corresponding faulty frequency is 100Hz), $f_0 = 30Hz$, $f_n = 4000Hz$, $\xi = 0.019894$ and the corresponding $B = 500$, $e(t)$ is a standard normal distribution with standard deviation 1.5. The sampling frequency $f_s = 20480Hz$, the sampling points are $N=4096$.

The simulation signal and its frequency spectrum are shown in Fig.2. The harmonic wave and impulsive components are mixed with the noise as well as the corresponding frequency spectrum.

It worth to point out here that if the noise level is higher than a certain ratio, for example, if the natural frequency $f_n = 4000Hz$ in Fig. 2 (b) is submerged by noise, it would be difficult to detect the faulty frequency for almost every signal processing method.

The parameters to run the EEMD are carefully chosen and suggested by Ref. [25], the noise level $N_l=0.3$, ensemble number $q=100$, and the number of prescribed IMFs is 8.



(a) The raw signal

(b) The frequency spectrum of the raw signal

Fig. 2. The raw signal and the corresponding frequency spectrum

All the computations are conducted using Matlab2010a on a laptop computer with a 2.5GHz CPU (Intel(R) Core (TM) I5-2450M) and 2.95GB memory. According to the TIC and TOC commands of Matlab2010a, the computing times required to finish the EEMD decomposition, RDT extraction and Hilbert envelope spectrum analysis are less than 1.76 seconds for several tests. This should be the quick enough for on-line detection of faults.

The EEMD decomposition results are shown in Fig.3. From IMF1 to IMF4, the impulse signal cannot be seen clearly. The frequency spectrum and the Hilbert envelope spectrum for the IMF1 are shown in Fig.4. In Fig.4.(a), only the two frequencies 4000Hz and 8000Hz are clearly seen. However, they do not reflect the feature frequency of the fault (the modulation frequency 100Hz and its harmonics). The feature frequency of the fault (100 Hz) and the second harmonic (200Hz), the shaft rotating frequency (30Hz), and other unknown frequencies, such as 80Hz, 235Hz, 290Hz, 425Hz and 490Hz are shown in Fig.4 (b). Therefore, the modulation frequency (100Hz) and the first harmonic 200Hz cannot be directly employed as the indicators to determine the fault. Furthermore, the frequency spectrum and the Hilbert envelope spectrum for the IMF2 to IMF7 are also obtained (not give in the paper) and all of them are not the sensitive indicators to reveal the fault.

To verify the performance of the present scheme for the extraction of impulse signal from the IMF1, IMF2 all of the other IMFs are employed to perform RDT and Hilbert envelope spectrum analysis. In the present, the data length is $\tau = 2048$. The triggering value x_s is suggested to $1.5\sigma_s$, [22-23], where σ_s is the standard deviation of the IMF. The impulse signal extracted by RDT and its Hilbert envelope spectrum for the IMF1 are shown in Fig. 5. From Fig.5(a), we can see clearly that the impulse response signal is shown up. As shown in Fig.5(b), the feature frequency (100 Hz) and the 2 to 5 harmonics (200Hz, 300Hz, 400Hz, 500Hz), the shaft rotating frequency (30Hz) will be robustly extracted.

Based on the above investigation, we conclude that the present approach using IMF1, RDT and Hilbert envelope spectrum can be employed to determine the periodical impulses (may represent faults of bearings and gears).

5. Experimental investigations

In this section, three laboratory experiments on rolling element bearings with inner race is conducted. The experimental setup (The machinery fault simulator-magnum, MFS-MG) is shown in Fig.6 as well as shown in Ref.[24]. The test system consisted of speed monitor, manual speed governor, acceleration sensors, speed sensors, motors, spindles and computer with DAQ software [24].

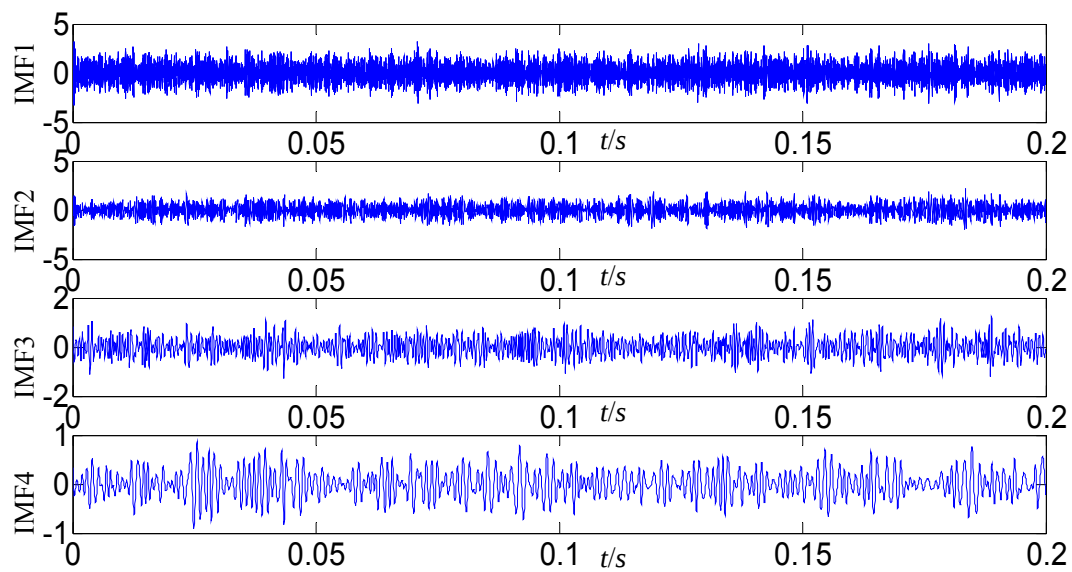
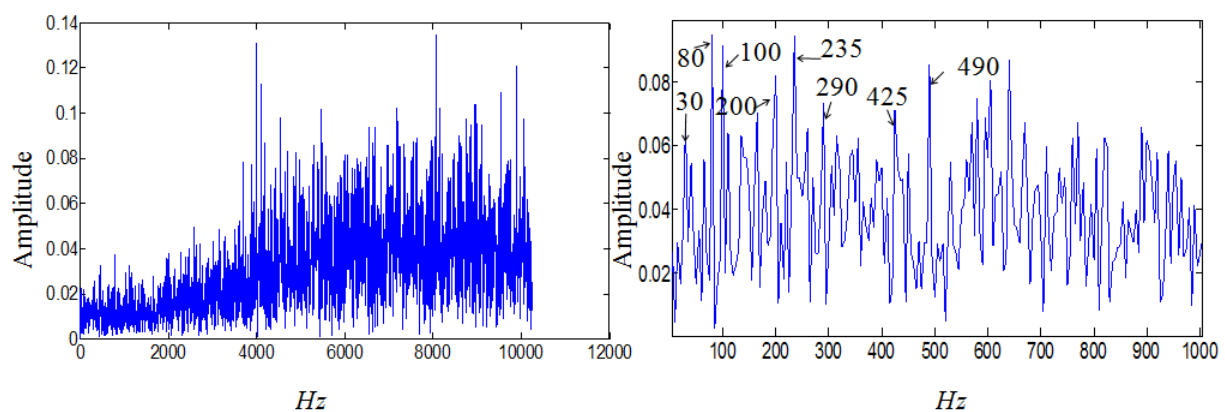
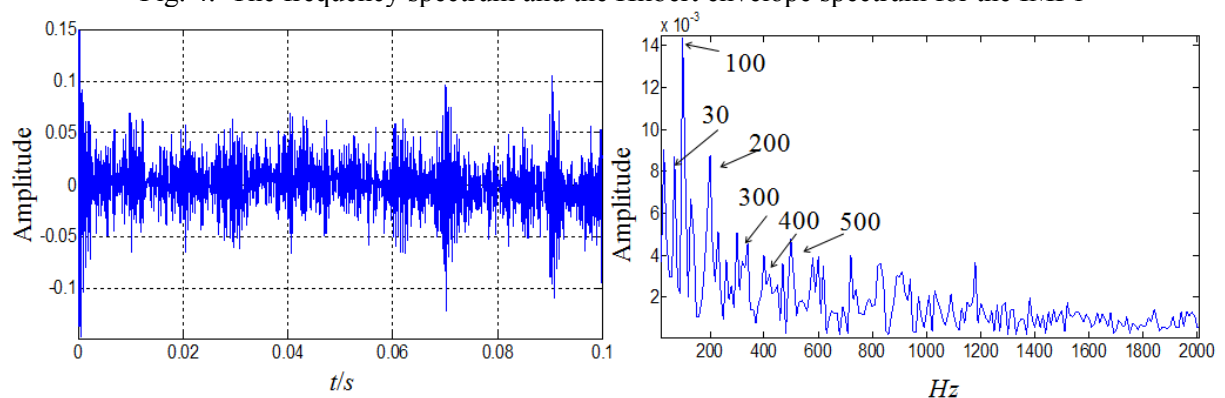


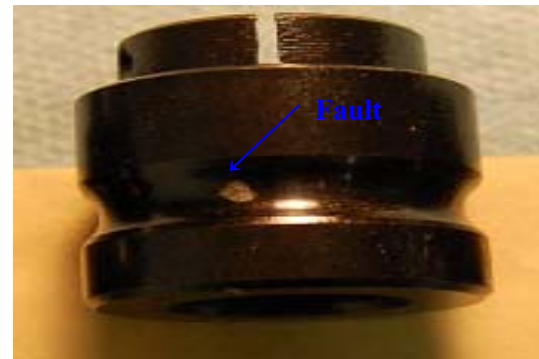
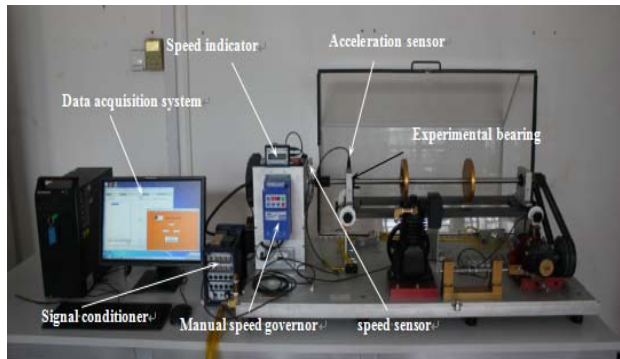
Fig. 3. The first four IMFs using the EEMD



(a) The frequency spectrum for IMF1 (b) The Hilbert envelope spectrum for IMF1
 Fig. 4. The frequency spectrum and the Hilbert envelope spectrum for the IMF1



(a) The impulse signal extracted by RDT from IMF1 (b) The Hilbert envelope spectrum
 Fig. 5. The impulse signal extracted by RDT and its Hilbert envelope spectrum for the IMF1



(a) The experimental setup

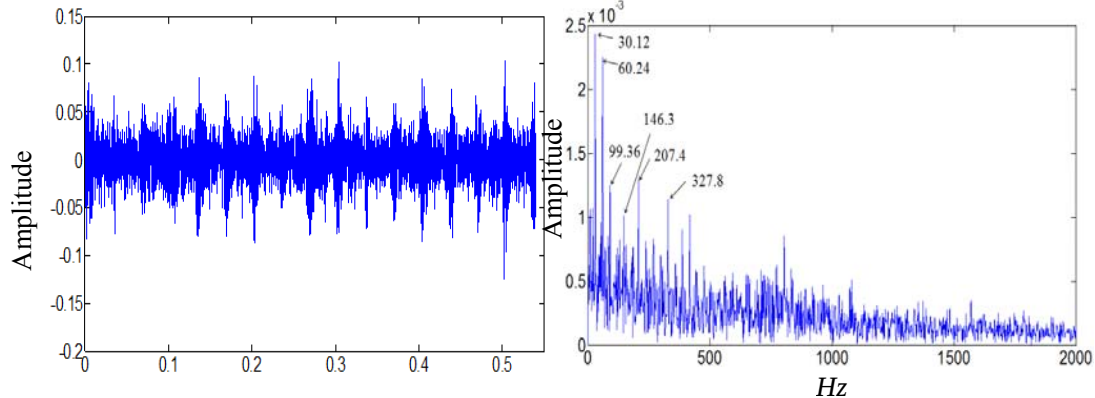
(b) The fault on the inner race of the bearing

Fig.6 The experimental setup and the fault on the inner race of the bearing

A deep groove bearing (ER-12K) was used in our experiment and the bearing parameters were: rolling element number $N_b = 8$, ball diameter $B_d = 0.3125$ inch, pitch diameter $P_d = 1.318$ inch, the contact angle $\alpha = 0^\circ$. In the experimental processing, the sampling frequency f_s was set to 25.6 kHz. For the bearing with inner race fault, the total collected data was 13824 points, the shaft rotating frequency $f_{shaft} = 30.12\text{Hz}$. Hence, the ball pass frequency of the inner race (BPFI) was [24]

$$BPFI = \frac{N_b}{2} f_{shaft} \left(1 + \frac{B_d}{P_d}\right) \cos \alpha = 4.9484 f_{shaft} = 149.05\text{Hz} \quad (15)$$

The raw signal is shown in Fig. 7(a). The present method was performed to detect the impulse response signal and further demodulate the feature frequency. The parameters to run the EEMD were similar to the numerical simulation example in Section 4, and the data length for the RDT analysis $\tau = 6800$. All the computations were conducted using the same laptop as shown in Section 4, and the computing times were less than 5.89 seconds for several tests.



(a) The raw signal

(b) The Hilbert envelope spectrum

Fig. 7. The raw signal and the corresponding Hilbert envelope spectrum for the IMF1

The Hilbert envelope spectrum of IMF1 is shown in Fig. 7 (b), and we find that shaft rotating frequency and its harmonics are equal to 30.12 Hz, 60.24Hz and 99.36Hz. The frequency 146.3 Hz might be the demodulated feature frequency, which is closed to the theoretical calculation value 149.05Hz (as shown in Eq.(15)). However, it is submerged in other frequency components, such as 207.4 Hz and 327.8Hz.

RDT analysis is conducted to IMF1 and the results are shown in Fig.8. As shown in Fig.8(b), the shaft rotating frequency $f_{shaft} = 30.12\text{Hz}$ and the second harmonic 60.24Hz, the feature frequency 148.7Hz and other frequency components, such as 178.8 Hz and 297.4 Hz are found. It is worth pointing out here that 297.4 Hz is exactly the harmonic of feature frequency; 178.8 Hz is exactly

the sum of the shafting rotating frequency (30.12 Hz) and the feature frequency (148.7 Hz). Moreover, the feature frequency 148.7Hz was matching with the theoretical calculation value 149.05 Hz. Therefore, the bearing with inner race fault was clearly detected.

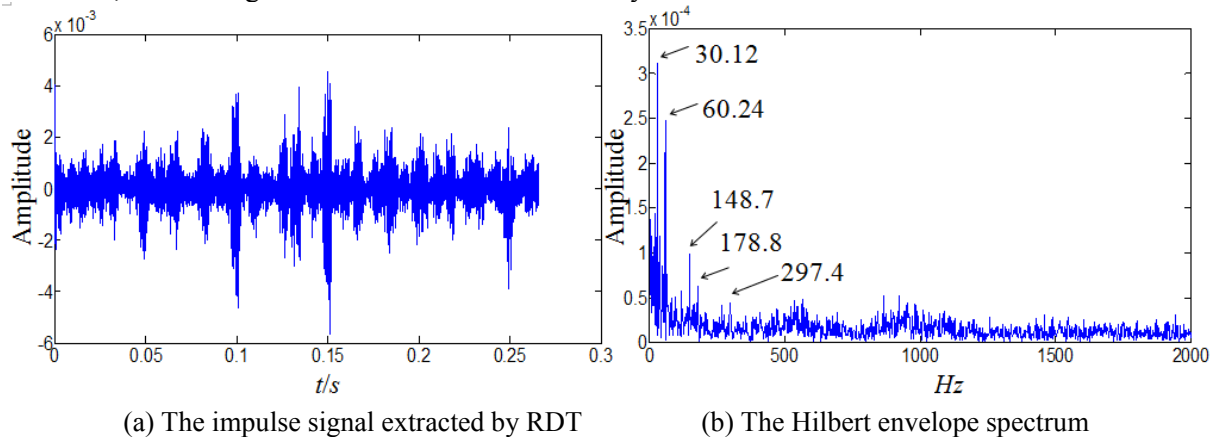


Fig. 8. The impulse signal extracted by RDT and its Hilbert envelope spectrum for the IMF1

6. Conclusion

In this paper, the good decomposition capability of the EEMD has been explored to decompose the non-stationary vibration signal. As we known, the vibrations of a bearing with faults are commonly the amplitude modulation signals, which are located at the high frequency band. More specifically, they often locate in IMF1 with heavy noises (mostly is random noise). Then, RDT is applied to analyze IMF1 to extract the fault induced impulse signals. Finally, the feature frequency of the faulty bearing or gear is obtained using the Hilbert envelope spectrum analysis. The main advantage of this method is its computational efficiency. This is reflected by the fact that it requires much less time, in comparison to the popular EEMD method, to achieve the same data analysis. The second advantage of this method is the well combination of the strong non-stationary vibration signal decomposition and impulse signal extraction abilities of the EEMD and the RDT, respectively. More specifically, the RDT can extract impulse signal from the stationary data only. Fortunately, IMF1 is exactly the stationary data. The third advantage is the fixed IMF1 is selected to perform Hilbert envelope spectrum analysis, which will overcome the difficult for EEMD analysis on how to select the optimal IMF. From the results of the numerical simulation and experiment investigation, it can be seen that the present method is suitable to detect impulse-dominated faults in mechanical systems.

Acknowledgments

The authors are grateful to the support from the National Science Foundation of China (Nos. 51575400, 51505339), the Zhejiang Provincial Natural Science Foundation of China (LQ16105005).

References

- [1] Khatir A, Tehami M, Khatir S and Abdel Wahab M 2016 *J. Vibroeng.* **18**(8) 5063– 5073.
- [2] Zhou Y-L, Maia NMM, Sampaio R and Wahab MA 2016 *Struct. Health Monit.* doi: 10.1177/1475921716680849.
- [3] Zhou Y-L, Maia N and Abdel Wahab M 2016 *J. Vib. Control* doi: 10.1177/1077546316674544.
- [4] Zhou Y-L and Abdel Wahab M 2016 *J. Vibroeng.* **18**(7) 4491-4499.
- [5] Khatir S, Belaidi I, Serra R, Abdel Wahab M and Khatir T 2016 *J. Vibroeng.* **18**(1) 202-213.
- [6] Khatir S, Belaidi I, Serra R, Abdel Wahab M and Khatir T 2015 *Mechanika* **21**(6) 472-479.
- [7] Gillich G-R, Praisach Z-I, Abdel Wahab M, Gillich N, Mituletu IC and Nitescu C 2016 *Shock Vib.* **2016**(Article ID 2086274) 10.
- [8] Lin J and Zhang AM 2005 *NDT&E Int.* **38** 421-427.
- [9] Chen JL, Zuo Ming J and Zi YY 2013 *Smart Mater. Struct.* **22** 095022.

- [10] Lei YG, Li NP, Lin J and Wang SZ 2013 *Sensors* **13** 16950-16964.
- [11] Antonia J and Randall RB 2006 *Mech. Syst. Signal Pro.* **20** 282-307.
- [12] Antonia J and Randall RB 2006 *Mech. Syst. Signal Pro.* **20** 308-331.
- [13] Li C and Liang M 2011 *Smart Mater. Struct.* **20** 045016.
- [14] Xiang JW, Zhong YT and Gao HF 2015 *Measurement* **75** 180-191.
- [15] Sun C, Zhang Z.S, Cheng W, He ZJ, Shen ZJ, Chen BQ and Zhang L 2013 *Smart Mater. Struct.* **22** 085012.
- [16] Bozchalooi IS and Liang M 2010 *Smart Mater. Struct.* **19** 075008.
- [17] Huang NE, Shen Z and Long SR 1998 *P. Roy. Soc. A-Math. Phy.* **454** 903-995.
- [18] Wu Z and Huang NE 2009 *Adv. Data Anal. Classi.* **1** 1-41.
- [19] Yeh JR, Shieh JS and Huang NE 2010 *Adv. Data Anal. Classi.* **2** 135-156.
- [20] Wang YH, Yeh CH and Young HWV 2014 *Phys. A.* **400** 159-167.
- [21] Cole HA 1986 *AIAA Paper*. **68** 288-319.
- [22] Ibrahim SR 1977 *J. Spacecraft Rockets.* **14** 696-700.
- [23] Ibrahim SR 1977 *AIAA Paper* **77** 1-9.
- [24] Li PF, Jiang YY, Xiang JW 2014 *Sci. World J.* **2014** 145807.