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A Vibration Signal Analysis Method based on Enforced De-Noising and Modified EMD

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Abstract

To deal with the noise from rotating machinery vibration signal and analysis the fault signal, a rotating machinery fault diagnosis method based on enforced de-noising and modified EMD is proposed. Firstly, fault signals were de-noised by the wavelet with enforced threshold in order to filter the noises in the high frequency, and then the EMD method used to decompose the fault signals into a finite number of stationary intrinsic mode function (IMFs), then the linear correlation coefficient between two sets of data is proposed to select the useful IMF. In order to restrain the endpoint effect of EMD, in this paper, the cosine window function is employ to the fault signals, and then the envelope error of the fault signals is controlled at the both endpoints of the vibration signals. Experimental results shows: this proposed method can extract the fault information effectively, with overcoming the drawbacks of EMD well.

Keywords: *Vibration signal, EMD, wavelet*

1. Introduction

Rotating machinery, one of the most common mechanical equipment, plays an important role in industrial production and national economy, but it can bring a serious consequence in industrial security and economy once the mechanical equipment did not well. So, in recent years, many researchers pay their attention to increase the reliability against possible faults for rotating machinery [1]. Some methods, based on analysis the vibration signal of rotating machinery, were one of the most effective and common used for fault diagnosis, were reported. Those methods were divided into four classes mainly: 1) time-domain based, such as dimensionless and combined dimensionless and other intelligent method [2-3];2) based on frequency-domain, such as [4]; 3) based on time-frequency analysis, such as wavelet, EMD, *etc.*, [5-6] 4) based on model, such as SVM, HMM, *etc.*, [7]. Although these methods based on frequency have obtained greater contribution on non-stationary signal analysis, they were easy to produce false signals and false frequency phenomenon when processing the vibration signal for rotating machinery. Wavelet analysis, which can provided the local features of the signal in both the time and frequency domain, has been widely used in the rotating machinery fault diagnosis [8-9]. However, the drawbacks of it are essentially an adjustable windowed Fourier transform and have not the capability of self-adaptive in nature. So, recently, a new self-adaptive signal analysis method, named empirical mode decomposition was used by Huang *et. al.*, [10], which based on the local characteristic time scale of the signal and can decompose a

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complicated signal into a number of intrinsic mode function (IMFs), can be applied to nonlinear and non-stationary signal, such as vibration signal of rotating machinery. It has been extensively studied and widely utilized in various areas, such as voice recognition, system control and medicine and biology. And many research achievements has been increasing reported over the past decade [11-12].

Although the EMD method shows outstanding performance in processing non-linear and non-stationary signals, the algorithm itself has some weaknesses, such as endpoint effects, sifting stop criterion, extremum interpolation, and model mixing, *etc*. In order to overcome these defects of EMD, many research paid attention to improve the EMD algorithm, and some achievements have reported recently, such as to restrain the end effects an extension method based on the gray prediction model and an neural networks method reported in [13], the wave continuation data obtained by waveform matching method, and it could show the trend of the signal well, the length of the wave continuation data was an arbitrary value, therefore these methods can not remove the endpoint effects well. Model mixing, was one of the outstanding shortcomings of EMD, which was defined as a single IMF including oscillations of dramatically disparate scales, or a component of a similar scale residing in different IMFs. It is result of signal intermittency. To solve the problem of mode mixing in the original EMD, an algorithm based on ensemble empirical mode decomposition(EEMD), was employed by Wu[14]. The EEMD was introduced based on the statistical properties of while noise. However, the representations for noise of rotating machinery fault diagnosis were not the while noise and the EEMD has high computational complexity, so the performance of EEMD dropped sharply when used in the actual vibration signal for rotating machinery. To make the EMD method being employ in online fault diagnosis systems, a low-complexity sinusoidal-assisted EMD algorithm reported in [15], however, how to treat the noise in signal was not mentioned. In order to filter the noise in the vibration signal, many methods based on wavelet packet transform were published [16-17], in these methods, wavelet packer transform used to filter the noise based on pre-set the threshold, such as soft threshold, hard threshold. To obtain the useful IMF, the relevance of each IMF and original signal used to analysis the authenticity of each IMF, such as EMD energy entropy [18]. The defects of the method based on entropy were not taking into account the linear relation between each IMFs.

According to the actual industrial machinery situation: the actual vibration signal of rotating machinery, is a non-stable and non-linear, and it has the properties of modulation and weak, and the information of fault characters were submerged in the strong background noise which was not the white noise really. The de-nosing methods based on wavelet such as soft threshold and hard threshold can non remove the high frequency noise well, and in the each IMFs, there were exited the linear relation which can used to discriminate the authenticity of each IMF. Combining the summarizations of all the above analyzing, in this paper, a vibration signal analysis method based on enforced de-noising and modified EMD is proposed. In this reported, to process the noise of actual rotating machine vibration signal, enforced de-noising method based on wavelet is employed to remove the high-frequency noise in which the fault information were flooded, and so a relatively pure signal with fault information is obtained. In order to improve the performance of EMD, in this proposed, a linear correlation coefficient method used to measure the relevance of each IMF and original signal and the cosine window function is used for the vibration signal to smooth the endpoint data and restrain the spread of the envelope of vibration signal.

The remainder of this paper is organized as follows. The algorithm of the proposed about enforced de-noising based on wavelet analysis, and the modified EMD based cosine window and linear correlation coefficient is described in the second section. In third section, the experimental setup and the experiment data for this paper are introduced

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detailed. The experiment results, performance analysis and comparisons are discussed in fourth section. Finally, in fifth section gives the final conclusion.

2. Algorithm Description Enforced De-noising and Modified EMD

2.1. Continuous Wavelet Transform

Wavelet transform, an adaptive, multi-resolution capability method, has made it be a powerful tool for rotating machinery fault diagnostics. Since then, this technique has been extensively employed and studied by various area researchers, and has obtained great progress. In this paper, the continuous wavelet transform (CWT) was employed, the introduction for others wavelet transform please refer to [19]. The introduction of continuous wavelet transform given as follows.

A given signal $x(t), x(t) \in L^2(R)$, the CWT of the given signal $x(t)$ was defined as:

$$W(a,b) = |a|^{-1/2} \int x(t)\Psi^*(\frac{t-b}{a})dt \tag{1}$$

In Eq (1), the symbols a and b denotes the scale factor and shift factor respectively. $\Psi^*(\bullet)$ Was the complex conjugate of the scaled and shifted wavelet function $\Psi(\bullet)$. And then, the function $\Psi_{a,b}(t)$, namely wavelet base function, which was defined as follows:

$$\Psi_{a,b}(t) = |a|^{-1/2} \Psi(\frac{t-b}{a}), a \in R, a \neq 0, b \in R \tag{2}$$

The difference between CWT and Fourier transform was two factors parameters contained in the family of wavelets, which was used to projected the signal into a two-dimensional, time-scale plane, instead of only one-dimensional plan of Fourier transform. A pair of Fourier transform and inverse Fourier transform can be achieved by below computational in Eq(1).the frequency domain of Eq(1) given as:

$$\begin{aligned} W(a,f) &= F\{W(a,b)\} \\ &= (2\pi)^{-1} |a|^{-1/2} \int_{-\infty}^{\infty} (\int_{-\infty}^{\infty} x(t)\Psi^*(\frac{t-b}{a})dt)e^{-j\omega b}db \\ &= |a|^{1/2} X(f)\Upsilon^*(af) \end{aligned} \tag{3}$$

In Eq(3), the $F\{\bullet\}$ denotes the operator of Fourier transform, $X(f)$ and $\Upsilon^*(\bullet)$ denotes the Fourier transform of $x(t)$ and $\Psi^*(\bullet)$, respectively. And then, the Eq (3) can be converted back into time domain by:

$$\begin{aligned} W(a,t) &= F^{-1}\{W(a,f)\} \\ &= |a|^{1/2} F^{-1}\{X(f)\Upsilon^*(af)\} \end{aligned} \tag{4}$$

Eq (4) indicated the CWT can be regarded as a band-pass filter with itself function and the performance for filtering controlled by the scale factor a .

2.2. EMD Method

EMD method was proposed by Huang, through the EMD method, the original signal was decomposed into many narrowband components, each of components was named an intrinsic mode functions. And they must satisfy the following definitions[10].

(1) In the whole data set, the number of extreme and the number of zero-crossings must either equal or differ at most by one.

(2) At any point, the mean value of the envelope defined by local maxima and the envelope defined by the local minima is zero.

A given time-series signal as $x(t)$, then obtained all the local extreme point of the signal $x(t)$, and its upper and low envelope value are defined as $u_1(t)$ and $v_1(t)$ through employed the cubic spline connected all the local extreme maxima value and all the local extreme minima value , respectively. The $m_1(t)$ function was the mean of upper and low envelope value is given as following:

$$m_1(t) = \frac{u_1(t) - v_1(t)}{2} \tag{5}$$

The first component $h_1(t)$ was defined as:

$$h_1(t) = x(t) - m_1(t) \tag{6}$$

If the first component $h_1(t)$ meets these conditions mentioned above, and then $h_1(t)$ was regarded as the first component of the given signal. However, if $h_1(t)$ can't meet the condition, and then $h_1(t)$ was treated as the new original signal, and repeated the above two equation; then after k times repeated, the function $h_k(t)$ becomes an IMF which was given as following:

$$h_k(t) = h_{k-1}(t) - m_{k-1}(t) \tag{7}$$

And in the iteration process of solving the IMF, the mean of upper and low envelope can be upgrade by following:

$$m_{k-1}(t) = \frac{u_{k-1}(t) - v_{k-1}(t)}{2} \tag{8}$$

First IMF $c_1(t)$ of original signal should contain the finest scale or the shortest period component of signal, and the rest of the signal $r_1(t)$ are obtained until $h_k(t)$ meet the conditions mentioned above which can be given as following:

$$c_1(t) = h_1(t) \tag{9}$$

$$r_1(t) = x(t) - c_1(t) \tag{10}$$

Regarded $r_1(t)$ as the new original, and then carried out the above iterations steps, the second IMF $c_2(t)$ of $x(t)$ was obtained, repeated the iteration n times, until the monotonic function $r_n(t)$ which can't extract the component that meet the IMF conditions, finished the iteration processing. And then the given signal $x(t)$ can be rewritten as:

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{11}$$

$r_n(t)$ Was the rest of the given signal $x(t)$ which denoted the signal stable trend. The Hilbert and marginal spectrum obtained by carrying out Hilbert transform for each IMFs, which had given as the follows[10]:

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$$c_{ii}(t) = \frac{1}{\pi}\int_{-\infty}^{\infty} \frac{c_i(t)}{t-\tau} d\tau \tag{12}$$

Then constructing the analytic signal as:

$$z_i(t) = c_i(t) + jc_{ii}(t) = a_i(t)e^{j\theta(t)} \tag{13}$$

Finally, the amplitude and phase function obtained as below, respectively:

$$a_i(t) = \sqrt{c_i^{\ 2} - c_{ii}^2(t)} \tag{14}$$

$$z_i(t) = c_i(t) + jc_{ii}(t) = a_i(t)e^{j\theta(t)} \tag{15}$$

The Instantaneous frequency obtained:

$$f_i(t) = \frac{w_i(t)}{2\pi} = \frac{1}{2\pi} \times \frac{d\theta(t)}{dt} \tag{16}$$

Then Hilbert transform and marginal spectrum defined as below, respectively:

$$H(w,t) = RP\sum_{i=1}^{n} a_i(t)e^{j\int w_i(t)dt} \tag{17}$$

$$h(w) = \int_0^L H(w,t)dt \tag{18}$$

Where RP denotes the operator of obtained real, and L denotes the length of signal.

2.3. Cosine Window Based Endpoint Processing

Endpoint effect is one of key issues affecting the performance of EMD, in the process of EMD decomposition, it can't be sure that the endpoint is the extreme point, which resulting the spline fitting error, with the deepening of the decomposition, the fitting error accumulated continuously, and spreading inward step by step, Leading to the decomposition becomes no meaning.

In order to restrain the endpoint effect, many researchers pay attention to solve the endpoint effect problem and obtained certainly progress. Up today, there were two mainly methods to restrain endpoint effect reported, one is others spline functions used to fit the curve and to obtain the local mean value for signal. Although some improvement in endpoint effect has obtained, its performance is not better than that of the cubic spline. The other is based on waveform extension for restrain the endpoint effect. Waveform extension was a self-adaptive method for restraining the endpoint effect, which extension the wave at the endpoint by the most similar sub-wave for the trend of the internal signal to endpoint. The computational cost of this kinds of endpoint effects restrained method was very high because of they need to analysis the signal wave for forecasting the trend of the wave entirely. In this paper, cosine window function used to restrain the endpoint effects, which was given as the follows:

$$w(t) = \begin{cases} \sin(\frac{\pi}{2} \times \frac{t}{A}) & 0 \le t \le A \\ \cos(\frac{\pi B}{2} \times \frac{t-B}{B}) & B \le t \le L \\ 1 & A < t < B \end{cases} \tag{19}$$

In Eq (19), the symbol A and B denotes the left endpoint and right endpoint, respectively. L Denotes the length of the signal.

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2.4. Linear Relation Measurement

In the processing of EMD, because of the false IMFs mixed into valuable IMFs, to obtain the valuable IMFs, many methods based on the correlation between original signal and the IMFs used to select the valuable IMFs. The correlation degree used to distinguish the valuable IMFs and false IMFs, this kinds of method were very useful in signal mixed with white noise. However, the noise, mixed in the actual rotating machinery vibration signals, was very complex and not represented by white noise only. To illustrate the energy of vibration signal changes with its frequency, a method based on EMD energy entropy was reported in [18], the results given in the reported were acceptable in the roller bearing out-race fault. However, in the processing of EMD, a linear correlation existed between each IMFs and the original signal, this kinds of correlation, especially, in actual vibration signal, represented obviously. In this proposed, a method based on linear correlation used to trace the correlation degree between IMFs and the original signal to distinguish the authenticity of each IMFs.

The linear correlation between each IMFs and the original signal given as following:

$$\rho_{lc}^{i} = \frac{\sum (c_i(t) - \overline{c}_i(t))(y(t) - \overline{y}(t))}{\sqrt{\sum (c_i(t) - \overline{c}_i(t))^2}\sqrt{\sum (y_i(t) - \overline{y}_i(t))^2}} \tag{20}$$

Where $c_i(t)$ denotes the ith IMF component, $y(t)$ denotes the original, $\overline{c}_i(t)$ and $\overline{y}(t)$ denotes the mean value of $c_i(t)$ and $y(t)$, respectively.

3. Experimental Setup

3.1. Experimental Platform

In this paper, our research lab (Guangdong province Petrochemical Equipment Fault Diagnosis Key Laboratory in Guangdong University of Petrochemical Technology, China) has put up a rotating machinery fault diagnosis experimental platform, and two patents about the experimental platform have been authorized by Patent Office of People's Republic of China. One of the real test beds which selected to obtain the experimental data illustrated in Figure 1. For more details about the parameters for each unit please referred to[20].

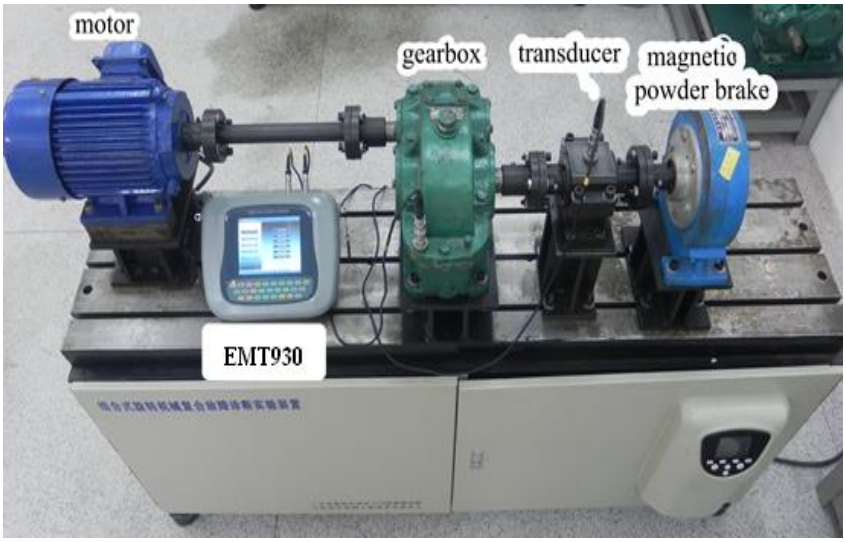

Figure 1. The Developed Real Test Bed

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EMT390 was vibration signal collection equipment for acceleration, velocity and displacement. The detailed parameters about vibration measurement given in Table 1, the temperature and rotation rate measurement given in Table 2 as follows, respectively.

Table 1. Parameters of Vibration Measurement Table about EMT390

	Measurement range		Frequency Range (Hz)		Accuracy (Word)
	Limit	Caps	Limit	Caps	
Acceleration	0.1 m/s2	199.9 m/s2	10	10K	±5%±2
Velocity	0.01 cm/s	19.99 cm/s	10	1K	
Displacement	0.001 mm	1.999 mm	10	1K	

Table 2. Parameters of Temperature and Rotation Rate Measurement about EMT390

	Limit	Caps	Accuracy(Word)
Temperature Measurement(℃)	0	400	1%±1
rotation rate(Rev/min)	1	6000	2‰±1

3.2. Experimental Data

The format of the vibration signal collected by EMT390 was '.dat', and the detailed information about its head file for each waveform data given in Table 3 as below.

Table 3. The Format Information of each Head for the Waveform

	Star	En	MPN	Pro	SP	CI	AT	FC	FL	SF	T	L
bit	1	1	2	1	1	3	2	1	2	2	5	1
Bitth (16)	1	2	3,4	5	6	7,8,9	0A, 0B	0C	0F, 10	11, 12	13-17	18
Bitth (10)	1	2	3-4	5	6	7-9	10-11	12	15-16	17-18	19-23	24

In the Table 3, MPN denoted the measurement point No, which was the fixed compression BCD code, pro denotes the property of vibration signal, such as 00 is acceleration 01 is velocity and 02 is displacement. SP was the sampling point, which was the BIN code,01 (512),02(1024),⋯,10H(8192).CI, AT, FC, FL, SF, T, L denoted the class interval, amplification times, frequency Caps, frequency Limit, scale factor and label, respectively. The ratio of A/D for acceleration, velocity and displacement given as following:

$$r_{acc} = \frac{v_c}{\sqrt{2} \times v_{AT} \times 10} \tag{21}$$

$$r_{vel} = \frac{v_c}{v_{AT} \times 100} \tag{22}$$

$$r_{dis} = \frac{v_c}{2 \times \sqrt{2} \times v_{AT} \times 1000} \tag{23}$$

Where the symbol r_{acc}, r_{vel}, r_{dis} denoted the true value of acceleration, velocity and displacement, respectively. v_c And v_{AT} represented the CI and the AT mentioned in Table 3.

In this proposed, the vibration signal of bearing internal crack were selected for experiment, the sampling frequency is 1 kHz. To analysis the performances of methods mentioned in this paper conveniently, in all the experiment, the first 1024 point used.

4. Discussions and Analysis

In this proposed, SNR (signal to noise ratio), used to evaluate the performance of the de-noising methods mentioned in this paper, which defined as:

$$SNR = 10\lg\left[\sum_{k=1}^{N} x^2(k) / \sum_{k=1}^{N} (x(k) - x_{emd}(k))^2\right] \tag{24}$$

where $x(t)$ and $x_{emd}(t)$ denotes the original signal and the signal after EMD de-noising. To reduce the affect from the layer and marginal effects of EMD, enforced wavelet de-noising based used to analysis the vibration signal. In this paper, db5 was employed. And the comparison of each de-noising methods mentioned in this paper and the proposed given as Figure 1.

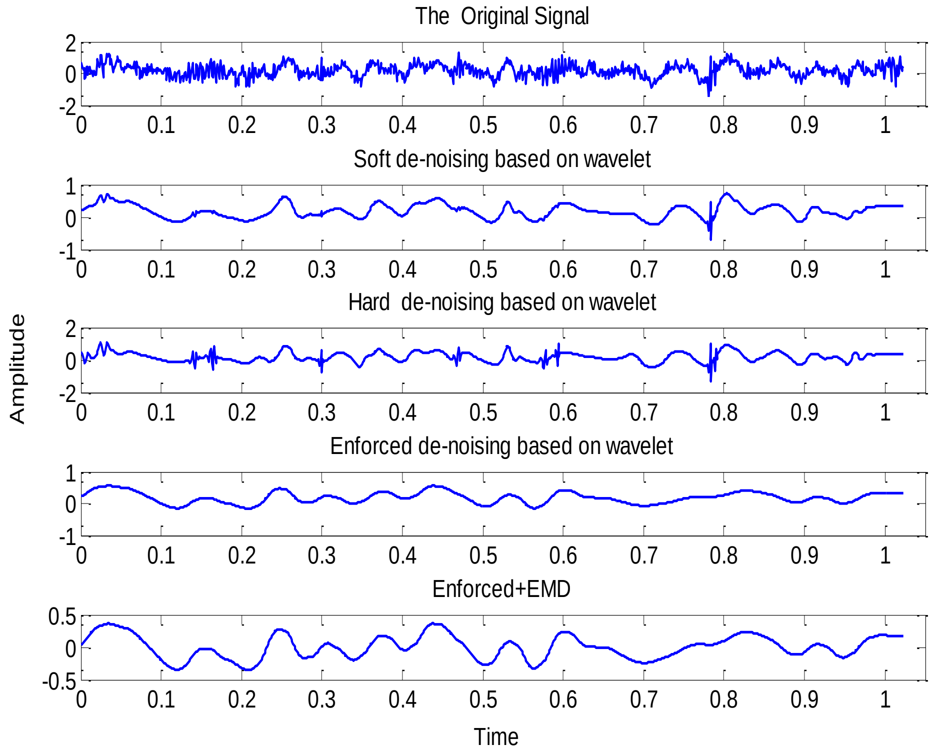

Figure 1. Comparison of Various Noise Reduction Methods

Illustrated from the Figure 1, it is seen that the two IMFs obtained by soft threshold de-noising based wavelet and hard threshold de-noising based wavelet are distorted seriously. The white noise and high frequency noise component in the vibration signal have been filtered well with employed the enforced de-noising based wavelet and EMD. The signal obtained from the de-noising method is closer to the actual machinery vibration signal which is the truly we want to.

And then, in order to estimate the quantity of the signal after filtered, SNR based analysis method employed to the obtained signal, and the detailed SNR given in the table 4 as the following:

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Table 4. The SNR for the Signal After Noise Reduction

	Soft De-noising	Hard de-noising	Enforced	Enforced+EMD
SNR	3.2416	1.2446	3.8829	7.1049

The Table 4 shows, comparing with these four methods mentioned, the SNR of the Enforced+EMD method is the highest. At the same time, representing the capable of the method for de-noising is stronger, relatively.

In this proposed, the cosine function window used to restrict the endpoint effect, comparing with the method based on waveform matching prolongation, the result given as the following:

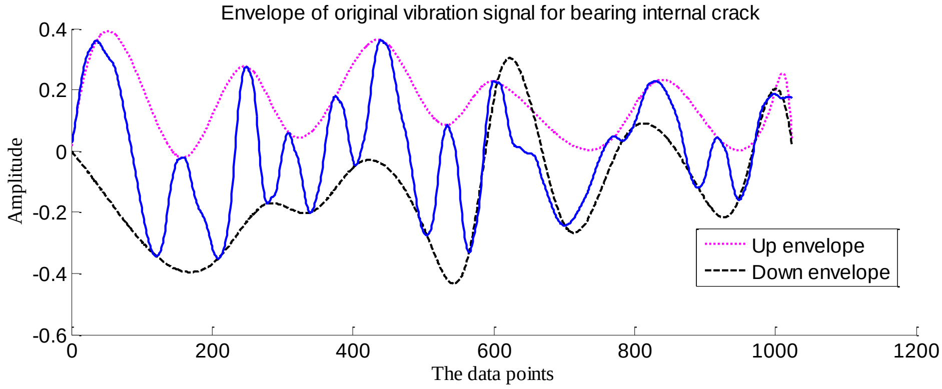

Figure 2. The Envelope of Original Signal

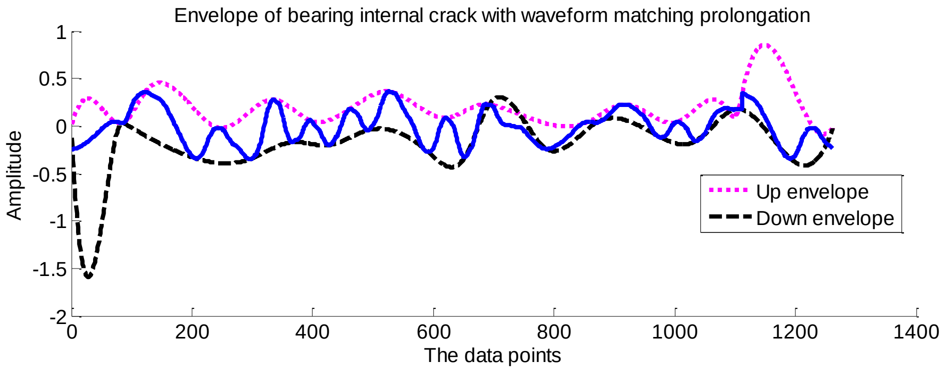

Figure 3. The Envelope of Bearing Internal Crack with Waveform Matching Prolongation

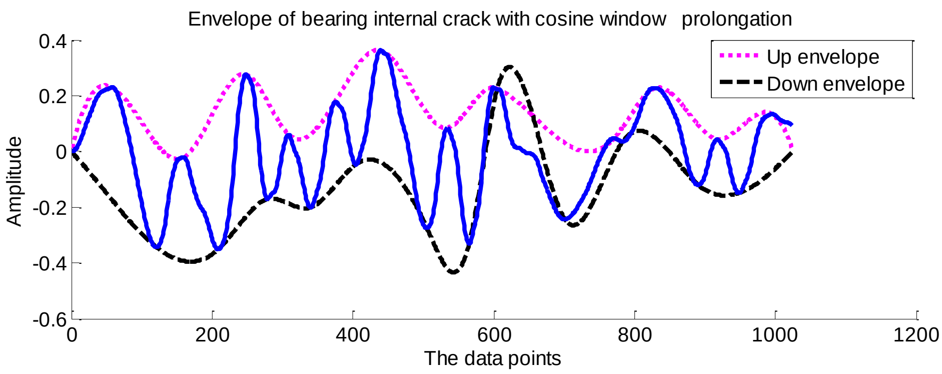

Figure 4. The Envelope of Bearing Internal Crack with Cosine Window Prolongation

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From the Figure 2 and Figure 3, at the endpoint of envelope obtained by waveform matching prolongation method, where have a serious problem about endpoint effect. However, illustrated from Figure 4, the serious endpoint problem was solved well by the cosine window prolongation method which provides a good protection to extract the IMFs accurately.

In order to analysis the performance of mentioned methods, the Hilbert spectrum and Marginal spectrum used to carry out comparing. The detailed Hilbert spectrum and Marginal spectrum for mentioned methods given as the follows:

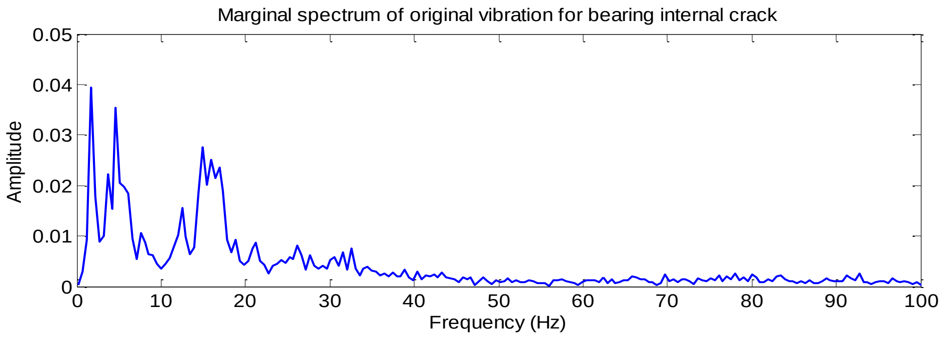

Figure 5. The Marginal Spectrum of Original Vibration Signal for Bearing Internal Crack

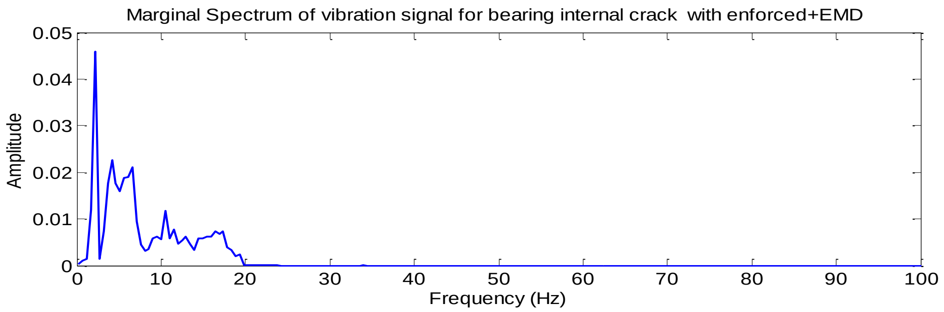

Figure 6. The Marginal Spectrum of Vibration Signal for Bearing Internal Crack with Enforced+EMD

Comparing with the Figure 5 and Figure 6 shows, in the original vibration signal of bearing internal crack, many noises hidden in the high frequency bands, and the high frequency noises were remove by the given method proposed in this paper.

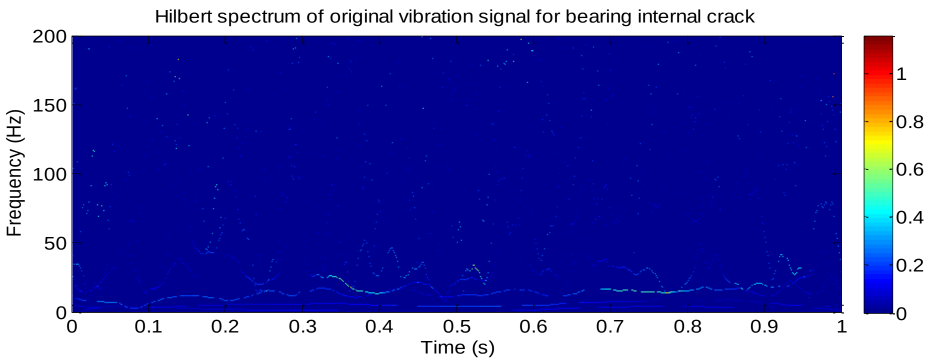

Figure 7. Hilbert Spectrum of Original Vibration Signal for Bearing Internal Crack

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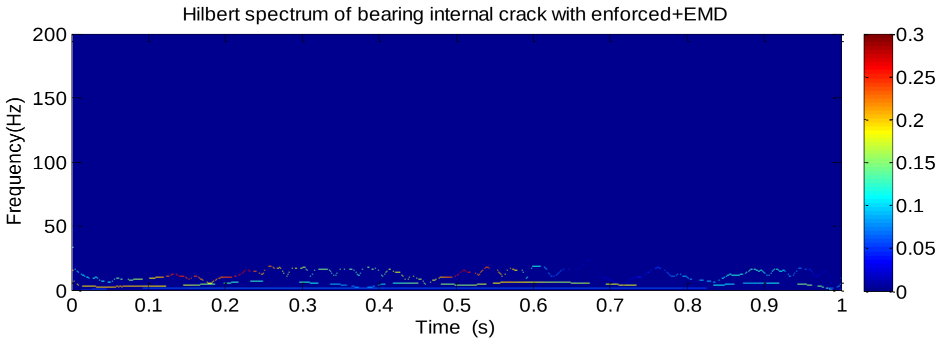

Figure 8. Hilbert Spectrum of Bearing Internal Crack with Enforced+EMD

Compared with the Figure 7 and Figure 8, the high frequency components from Figure 7 is obvious that of from Figure 8. In the Figure 7, the high frequency components was produced by the background noises, which effecting the performance of the signal processing method.

5. Conclusion

In this paper, a new method based on wavelet and modified EMD for vibration signal analysis was proposed. First, according to distribution of the noises in the actual vibration signal with some fault occurring, we employed the enforced de-noising strategy of wavelet for the original bearing internal crack signal to remove the high frequency noises; then, the cosine window used to improve the endpoint effect of EMD method and linear correlation method used to resolve the mode mixing of EMD. From the result shows, the proposed method has a good ability of remove noises and good performance for EMD, however, the improvement of EMD performance is not perfect, a long way will to go in the future for fault diagnose based on EMD method.

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References

[1] S. Nandi, H. A. Toliyat and L. Xiaodong, "Condition monitoring and fault diagnosis of electrical motors-a review", Energy Conversion, IEEE Transactions, vol. 20, no. 4, **(2005)**, pp. 719-729.
[2] H. Louis Langhaar, "Dimensional analysis and theory of models", Place Published: Wiley New York, **(1951)**.
[3] W. Jiang and S. Liu, "Experimental research on sensitivity of dimensionless indexes in amplitude domain to hydraulic pump faults", Journal of Yanshan University, vol. 5, no. 3, **(2010)**.
[4] R. Isermann, "Model-based fault-detection and diagnosis – status and applications", Annual Reviews in Control, vol. 29, no. 1, **(2005)**, pp. 71-85.
[5] A. Bouzida, O. Touhami, R. Ibtiouen, A. Belouchrani, M. Fadel and A. Rezzoug, "Fault Diagnosis in Industrial Induction Machines Through Discrete Wavelet Transform", Industrial Electronics, IEEE Transactions, vol. 58, no. 9, **(2011)**, pp. 4385-4395.
[6] A. Komaty, A.-O. Boudraa, B. Augier and D. Daré-Emzivat, "EMD-Based Filtering Using Similarity Measure Between Probability Density Functions of IMFs", **(2014)**.
[7] Y. Yang, D. Yu and J. Cheng, "A fault diagnosis approach for roller bearing based on IMF envelope spectrum and SVM", Measurement, vol. 40, no. 9, **(2007)**, pp. 943-950.
[8] T. W. S. Chow and S. Hai, "Induction machine fault diagnostic analysis with wavelet technique", Industrial Electronics, IEEE Transactions, vol. 51, no. 3, **(2004)**, pp. 558-565.

[9] S. Wang, W. Huang and Z. K. Zhu, "Transient modeling and parameter identification based on wavelet and correlation filtering for rotating machine fault diagnosis", Mechanical Systems and Signal Processing, vol. 25, no. 4, **(2011)**, pp. 1299-1320.
[10] N. E. Huang, "The empirical mode decomposition and the hilbert spectrum for nonlinear and non-stationary time series analysis", Pro.R.Soc.Lond .A, vol. 454, **(1998)**, pp. 903-995.
[11] Y. Lei, J. Lin, Z. He and M. J. Zuo, "A review on empirical mode decomposition in fault diagnosis of rotating machinery", Mechanical Systems and Signal Processing, vol. 35, no. 1, **(2013)**, pp. 108-126.
[12] A. Tabrizi, L. Garibaldi, A. Fasana and S. Marchesiello, "Influence of Stopping Criterion for Sifting Process of Empirical Mode Decomposition (EMD) on Roller Bearing Fault Diagnosis", Place Published: Springer, **(2014)**.
[13] H. Zhou, G. Jun Liu, J. Qiu and K. Hong Lv, "Intermittent Fault Diagnosis under Extreme Vibration Environment Based on EMD and Neural Network", Key Engineering Materials, vol. 584, **(2014)**, pp. 97-101.
[14] S. Wang, W. Huang and Z. K. Zhu, "Transient modeling and parameter identification based on wavelet and correlation filtering for rotating machine fault diagnosis", Mechanical Systems and Signal Processing, vol. 25, no. 4, **(2011)**, pp. 21.
[15] W.-C. Shen, Y.-H. Chen and A.-Y. Andy Wu, "Low-complexity sinusoidal-assisted EMD (SAEMD) algorithms for solving mode-mixing problems in HHT", Digital Signal Processing, vol. 24, **(2014)**, pp. 170-186.
[16] D. Donoho, "Denoisingbysoft-thresholding", IEEETransactionsonInformationTheory, vol. 41, **(1995)**, pp. 613–627.
[17] A. VasilyStrela and A. T. Walden, "Signal and image denoising via wavelet thresholding:orthogonal and biorthogonal,scalar and multiple wavelet transforms", **(1998)**.
[18] Y. Yu and C. Junsheng, "A roller bearing fault diagnosis method based on EMD energy entropy and ANN", Journal of sound and vibration, vol. 294, no. 1, **(2006)**, pp. 269-277.
[19] R. Yan, R. X. Gao and X. Chen, "Wavelets for fault diagnosis of rotary machines: A review with applications", Signal Processing, vol. 96, **(2014)**, pp. 1-15.
[20] Q.-H. Zhang, Q. Hu, G. Sun, X. Si and A. Qin, "Concurrent Fault Diagnosis for Rotating Machinery Based on Vibration Sensors", International Journal of Distributed Sensor Networks, **(2013)**.

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