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A Vibration Signal Envelope Extract Method Based on Wavelet

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Abstract

Rotating machine fault detecting is the key technology for ensure that they can run health and security. And the simple and practice methods based on envelope employed in the fault detecting. In this paper, a vibration signal envelope extract method based on wavelet was proposed. In this proposed, the wavelet used to filter the noise which embedded the vibration signal, and to detect weak signal (fault signal) through obtained the coefficients by wavelet processing. And then, the Hilbert envelope was introduced to do energy envelope spectrum analysis for coefficients obtained by wavelet processing, the results analysis shows, the proposed method used to extract the signal envelope for fault detecting is practical, stability and reliable.

Keywords: *Fault diagnosis; Hilbert transform; Wavelet analysis; Envelope extract*

1. Introduction

With the continuous improvement of complexity of engineering system, its reliability and safety are also put forward higher requirements. Fault diagnosis technology, based on system health status were analyzed to judge the type of diagnosis, is a special technical used to provides a scientific evidence for maintaining the machinery system on time and effective [1]. So, it has a good application prospect, especially in higher security requirement area, such as aerospace, shipbuilding. In particular, rotating machinery equipment (such as rotary bearing, steam turbine, compressor, blower, *etc.*,) is the important and key equipment in the fields of petroleum oil, chemical industry, metallurgy, machinery manufacturing, aerospace [2], *etc*. Therefore, researching on these methods of fault diagnosis for this kind of equipment has been a hot field. In rotating machinery fault diagnosis research is usually based on time domain or frequency domain analysis of vibration monitoring data of fault diagnosis [3]. Rotating machinery in the event of a failure, however, tend to have a large number of nonlinear vibrations monitoring signal, random, not traverse information, and bring great difficulty in fault signal analysis [4-5]. Considering the time domain vibration signal is the most basic of the original signal, if you can directly through this kind of time domain signals to extract fault features, fault diagnosis, to maintain the basic characteristics of the signal will be very beneficial [6].

Machinery fault diagnosis is the middle of the 20th century began to new and rapid development of a technology. During the early years of development, technology application is only confined to nuclear power, aerospace and aviation, *etc.*, high in the industry, but with the development of diagnostic technology, has already begun in the petrochemical, metallurgical and electronic industries rapid development. At present, the subject has been mature, and gradually penetrated into all walks of life. Due to mechanical failure signals belongs to small, easily with the other frequency signal mixed

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together, simple is difficult to be distinguished. However, is usually a signal these tiny implied a lot of information which can help us to found and to solve the problem in advance[7].

The fault feature information extraction is the most important in the mechanical fault diagnosis, one of the most critical problems. It is directly related to the accuracy of fault diagnosis and early fault forecasting reliability. Past the commonly used mechanical fault diagnosis method is Fourier analysis and complex spectrum, short time Fourier analysis, the winger distribution, *etc.*, [2]. However, these early use of methods are limited to a smooth, linear analysis in time domain, for the fault signal in the practical application can not be accurately reflects the characteristics of non-stationary signal.

Characteristics of signal envelope demodulation method, is commonly used in a square demodulation and envelope demodulation based on Hilbert transform[8], based on the wavelet envelope demodulation method. Square demodulation relative using the Hilbert transform to extract the signal envelope, use more long time. However, square demodulation method is slowly being abandoned by people because of its limitations. The Hilbert transform demodulation method is more advantage than square demodulation, to analyze the input signal in the frequency domain. And this is square demodulation can't do it.

The Hilbert transform and square demodulation as already mature and finalize the design method, and the existence of its relatively large limitations. Wavelet analysis as a demodulation method is emerging in recent years, increasingly clear its superiority. Relatively than the Hilbert transform envelope and wavelet transform of image information can be seen more intuitively. Signal singularity can through to the signal after wavelet transform under different scales of integrated performance, reflect the characteristics of the signal mutation or transient. This article through to the above method, compare method results, and the corresponding conclusions.

The remainder of this paper is organized as follows. The algorithm of the proposed about vibration signal envelope extract based on wavelet analysis, and the Hilbert envelope is described in the second section. In third section, the experimental setup and the results, analyses are discussed in third section. Finally, in fourth section gives the final conclusion.

2. Wavelet and Envelope

2.1. Wavelet Envelope

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 [1, 9-10]. Then the introduction of continuous wavelet transform given as follows.

Under the non-stationary conditions, set $\psi \in L^2 \cap L^1$ and $\hat{\psi}(0) = 0$, it can generate a family of wavelet functions $\{\psi_{a,b}\}$, which given as following:

$$\psi_{a,b}(t) = |a|^{-\frac{1}{2}} \psi\left(\frac{t-b}{a}\right), \qquad b \in R, a \in R - \{0\} \tag{1}$$

Then, it's defined as the analysis wavelet or the continuous wavelet, a is the scale factor, b is the time factor, $\psi(\cdot)$ called the basic wavelet or mother wavelet. The result of given signal and its wavelet analysis convolution was defined the continuous wavelet transform of the given signal.

And then, the continuous wavelet transform (CWT) of a given signal can define as follow:

$$(W_{\psi} f)(a,b) = |a|^{-\frac{1}{2}} \int_{-\infty}^{+\infty} f(t)\bar{\psi}(\frac{t-b}{a})dt \tag{2}$$

The basic wavelet $\psi(\cdot)$ satisfied the following permitting conditions:

$$C_{\psi} = \int_{R} |\omega|^{-1} |\hat{\psi}(\omega)|^{2} d\omega < \infty \tag{3}$$

where $\hat{\psi}$ is the Fourier transform of ψ, $(W_{\psi} f)(a,b)$ is the wavelet coefficients, and then its inverse transform is defined as:

$$f(t) = \frac{1}{C}\int_{-\infty}^{+\infty}\{\int_{-\infty}^{+\infty}(W_{\psi} f)(a,b)\left[\frac{1}{\sqrt{a}}\psi(\frac{t-b}{a})\right]db\}\frac{da}{a^{2}} \tag{4}$$

when ψ is a real function, and $a > 0$, then its rewritten as:

$$f(t) = \frac{2}{C}\int_{0}^{+\infty}\{\int_{-\infty}^{+\infty}(W_{\psi} f)(a,b)\left[\frac{1}{\sqrt{a}}\psi(\frac{t-b}{a})\right]db\}\frac{da}{a^{2}} \tag{5}$$

from the condition $\psi(t) \in L^{1}(R)$, the following equation can be obtained:

$$\int_{R} |\psi(t)| dt < \infty \tag{6}$$

A conclusion obtained that $\psi(t)$ has attenuation, from permit condition the following equation can be obtained:

$$\hat{\psi}(0) = \int_{R} \psi(t)dt = 0 \tag{7}$$

So, the $\psi(t)$ has volatility and band pass features.

From the above analysis, the definition of the wavelet transform in the frequency domain is equivalent to using a family band-pass filter to filter the signal. Meanwhile, the wavelet transform has the features of translation and stretch, according with the relationship of each factor, in the time domain and frequency domain the wavelet analysis has some limitations. But, when the wavelet analysis was regard as the filter banks, the temporal resolution must increase with the center frequency of the analysis filter. Thus, the frequency resolution may be allowed is proportional to the center frequency f, which given as following:

$$\frac{\Delta f}{f} = C \tag{8}$$

where C is a constant, therefore, the bandwidth and center frequency of the band pass filter wavelet is proportional. Or, the quality of the wavelet bandwidth of the band pass filter and the filter factor Q (center frequency / bandwidth) and center frequency are independent. So, the wavelet transform can be regarded as a constant Q analysis.

There are two ways to obtain the envelope of a given signal, one is to obtain the range of the band pass by adjust the scare factor a; the other is to use wavelet filter band pass, frequency selection to achieve the envelope signal resolution. The signal envelope demodulation processing figure shows as follows Figure 1.

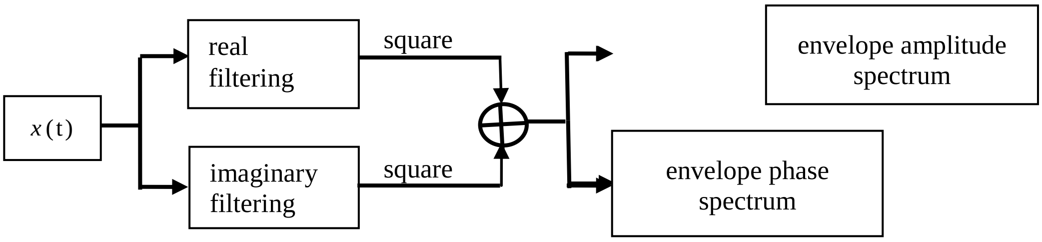

Figure 1. Envelope Demodulation Processing

2.2. Square Envelope Demodulation

In this kind of method, firstly, for the input signal, it was carried out the carrier modulation processing, then square deal for itself. This makes the energy for half of signal energy up to higher frequency range, while the other half of signal is converted to direct-current, which means that the negative components in the signal were removed, and then the signal was pre-emphasis processing and then low-pass filtering processing for the signal in order to filter the high frequency components. The envelope demodulation process was given as Figure 2.

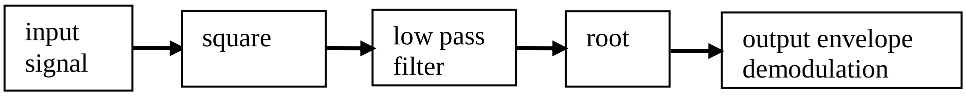

Figure 2. The Demodulation Process for Square

This method for extracting the envelope of signal is relatively simple, which just only need low-order filters can achieved. It also could be easily implemented in real hardware circuit. However, it is easy to cause data loss, which leads to a big error result. At the same time, due to the external disturbance, it has the fatal defect of stability and reliability.

2.3. Hilbert Envelope

The rotary machine fault signal obtained is a real signal in the time domain signal. However, the Hilbert transform was based on Fourier Transform which can bring the negative frequency components, so the Hilbert transform bring a lot of trouble to signal analysis. And many researchers do their best to improve the performance of Hilbert transform. In really, the analytic signal was introduced in signal analysis.

Given a continuous signal $x(t)$, its Hilbert transform $\hat{x}(t)$ was defined as:

$$\hat{x}(t) = \frac{1}{\pi}\int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau} d\tau = x(t) * \frac{1}{\pi t} \tag{9}$$

From Eq(9), it can be known $\hat{x}(t)$ obtained by the signal $x(t)$ pass through a filter $\frac{1}{\pi t}$ approximately. From the Fourier transform theory, it can be drawn that the substance of the Hilbert transform is let the signal produced 90 degree phase shift.

The analytical signal $z(t)$ is a complex signal; it contains the real and imaginary parts. The analytical signal $z(t)$ can defined as:

$$z(t) = x(t) + j\hat{x}(t) \tag{10}$$

Its frequency domain function defined as:

$$Z(t) = X(\omega) + j\hat{X}(t) \tag{11}$$

Where:

$$\hat{X}(\omega) = \int_{-\infty}^{\infty} x(t) e^{-j\omega} dt \tag{12}$$

From the convolution theorem and Fourier transform, the Hilbert transform $\hat{x}(t)$ rewritten as:

$$\begin{aligned} \hat{x}(t) &= x(t) * \frac{1}{\pi t}[F(\frac{1}{\pi t}) - j\,\mathrm{sgn}(\omega)] \\ &= -\frac{1}{\pi}\int_{-\infty}^{\infty} \frac{x(t-\tau)}{\tau} d\tau \end{aligned} \tag{13}$$

Its inverse transform given as:

$$x(t) = \hat{x}(t) * \frac{1}{\pi} = -\frac{1}{\pi}\int_{-\infty}^{\infty} \frac{\hat{x}(t-\tau)}{\tau} d\tau$$

The amplitude of the given signal $x(t)$ defined as:

$$A(t) = \left| z(t) \right| = \sqrt{x^2(t) + \hat{x}^2(t)} \tag{14}$$

In Eq(14), $A(t)$ is defined as the Hilbert transform envelope of the signal. Hilbert transform solution envelope process as shown in Figure 3.

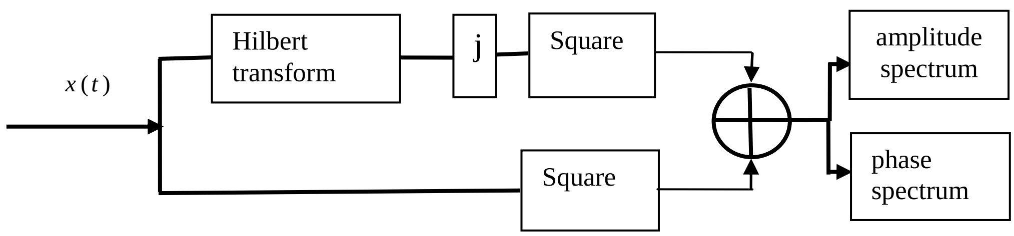

Figure 3. Hilbert Envelope Processing Figure

3. Experiment Set Up and Results Analysis

3.1. Experimental Setup

In this paper, a rotating machinery fault diagnosis experimental platform has been put up by our research lab (Guangdong province Petrochemical Equipment Fault Diagnosis Key Laboratory in Guangdong University of Petrochemical Technology, China), 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 4. For more details about the parameters for each unit please referred to[2]

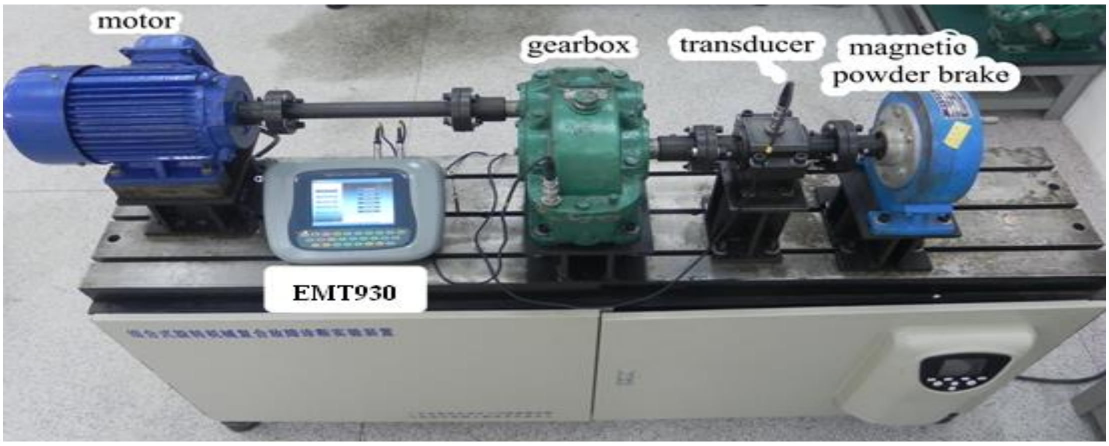

Figure 4. The Developed Real Test Bed

EMT390 used to obtain the vibration signal, such as 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

In this paper, the vibration signal of bearing wear collected by EMT390 used for analysis the performance of those methods mentioned above. The detailed bearing wear was given as the Figure 5.

Figure 5. The Bearing Wears Figure

3.2. Results Analysis

Rotating machinery fault signal obtained by EMT309, in the processing of the experiment, the wavelet function 'DB3' used to extract the envelope for the condition of health bearing and the bearing wear, respectively. The detailed results were given in the Figure 6 as following.

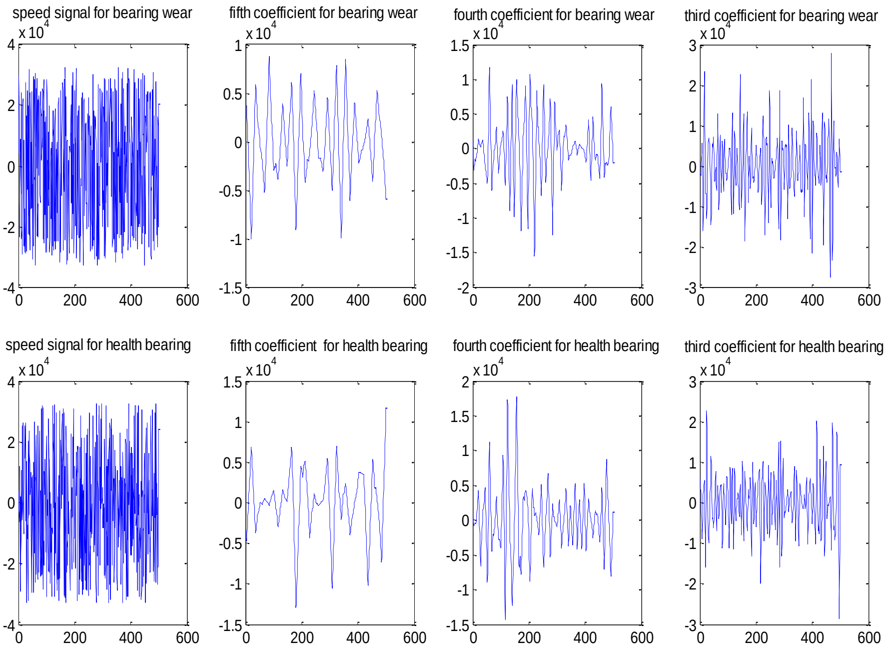

Figure 6. The Wavelet Coefficient for Health Bearing and Bearing Wear

From the Figure 6 shows, the fifth coefficient has better ability to distinguish the health bearing and bearing wear, especially, the amplitude of the fifth coefficient for health bearing is bigger than that of bearing wear which can used distinguish the fault or not. The discrimination ability of the fourth coefficient is worse than that of fifth coefficient, although, the fourth coefficient of health bearing is smoother than that of bearing wear. At the same time, the worst ability of discrimination is the third coefficient of wavelet. Because of the fault signal is very weak, which lead to the lower wavelet coefficient hard to handle this kind of signal accurately.

In order to analysis the performance of the mentioned methods, the Hilbert envelope were extracted with these wavelet coefficients, the detailed result given in the Figure 7 as the following.

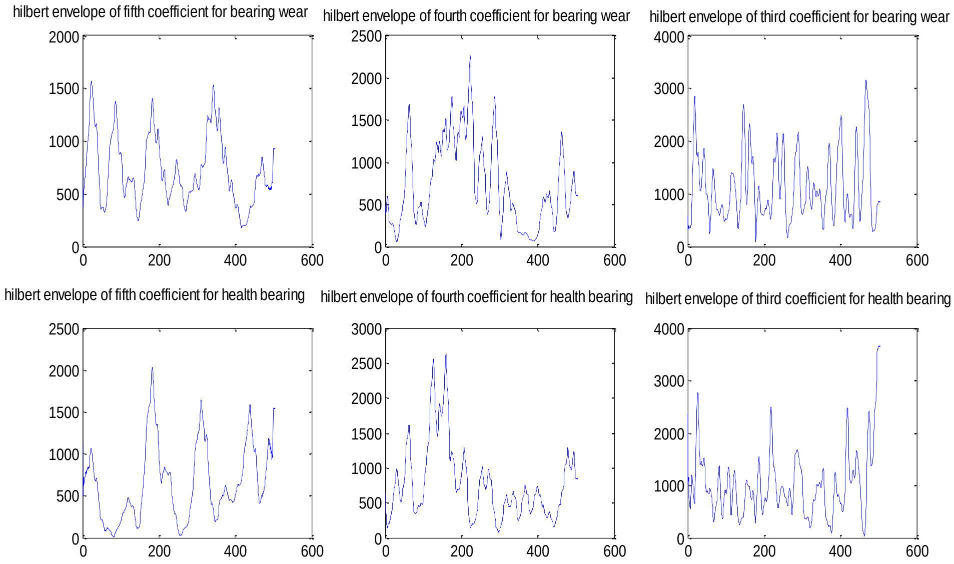

Figure 7. The Hilbert Envelope for Wavelet Coefficients

From the Figure 7 illustrated, the amplitude of the Hilbert envelope of fifth coefficient for bearing wear is stable relatively, however, that of for health bearing is not stabilization, which can used to distinguish the fault from rotating machine, but the distinguish ability is very weak. The amplitude of Hilbert envelope of fourth coefficient for bearing wears were concentrated on rang of 1000 or so, while that of health bearing were centered on 500. And the amplitude of Hilbert envelope of fourth coefficient for health bearing has a peak between 100 and 200. The peak came from the health bearing signal which used to detect the fault taken place or not. In the third coefficient, the Hilbert envelope energy amplitude for bearing wear were concentrated on up the 1000, while that of health bearing were below the 1000, the energy of Hilbert envelope get a drift.

4. Conclusion

In this paper, a new algorithm for envelope extracting based on wavelet, is proposed. The 'DB3' wavelet used to extract the coefficient for fault signal and health signal, and then the Hilbert envelope methods used to extract the envelope energy for fifth coefficient, fourth coefficient and third coefficient. This kind of envelope extracting method can used to detect the fault taken place, from the analysis of results, the envelope extracted from the proposed method, has the ability of fault detect, but this kind of method based envelope for fault detecting for rotating machine has not perfect performance.

So, the results show there is a long way to go in the field of fault diagnose, fault forecasting and fault detecting. Although, a little progress we have made, however, because of the fault signal very weak and the fault feature can not be found, So the performance of this proposed does not meet the actual requirements for the rotating machine fault detecting in industry, and then methods of better performance are the direction of our efforts.

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