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FAULT FEATURE EXTRACTING FOR ROTATING MACHINERY VIBRATION BASED ON BLIND DECONVOLUTION AND SPECTRAL KURTOSIS

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ABSTRACT

Rotating machinery vibration analysis involves a convolute mixture because of the propagation medium, and the signals recorded by sensors in an industrial application are often disrupted by the environment. Deconvolution is a signal processing method for convolution of vibration sources, spectral kurtosis is a statistical tool which can indicate the presence of series of transients and their locations in the frequency domain in strong noise case. In this paper, we propose an approach for the two characteristics based on blind deconvolution and spectral kurtosis. First the two methods blind deconvolution and spectral kurtosis are reviewed, and then puts forward the combination of the two methods to extract the fault feature from multi-sources convolution and strong noise in rotating machinery vibration, Finally apply the combination method to a bearing failure test, the test results show good performance for extraction of fault features in rotating machinery vibration.

Keywords: *Blind Deconvolution, Spectral Kurtosis, Rotating Machinery Vibration*

1. INTRODUCTION

Rotating machine is one of the most important equipments in industrial applications, such as bearings, gears. Their unexpected failures may endanger normal machine operation and productivity, it may cause significant economic losses. Vibration signal is easy to gather and is highly correlative with working conditions of rotating machines, because of these advantages, vibration analysis is usually used for condition monitoring and fault diagnosis.

In past decades, many classic methods have been proposed to extract fault feature from vibration signal, such as time-domain analysis, frequency-domain analysis, high-order cumulant spectrum analysis, short-time Fourier transform(STFT)[1], wavelet transformation[2-4], etc. Recently, several new method were proposed to increase the pattern of vibration signal processing such as empirical mode decomposition(EMD)[5], local mean decomposition(LMD)[6], etc. Rotating machinery vibration has its characteristics: the multi-vibration sources are convoluted with each other, the background noise is strong.

Rotating mechanical system are complex, and the vibration source are more than one, the propagation path of vibration is complex too, the signal is to be convoluted with each other. Because of the complexity of machine working condition and system structure, consider reducing the effect caused by the superposition of time-delay at transmission, many research use blind deconvolution[7-9] processing method for enhancing and extracting the fault features.

As a commonly used method on the fault diagnosis in strong noise case, resonance demodulation[10] has its limits: the selection of band-pass filter parameters depends on the operator's experience and historical data, it need to try lots of times, that is cost lots of time at the system with several rotating components. Spectral kurtosis[11,12] can determine the best band-pass filter parameters automatically, combined with spectral analysis, it can do a better job in fault diagnosis.

In this paper, we propose a method to detect the rolling bearing fault based on blind deconvolution and spectral kurtosis. We pretreatment the signal with blind deconvolution to enhance the impulse signal, then design the best band-pass filter by calculating spectral kurtosis and analyze the filtered signal by using spectral analysis.

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2. NEW APPROACH THEORY

2.1. Blind Deconvolution

When the bearing is rolling, the damage place of the component will generate impulse intermittently, which delivered to sensor by a unknown channel. Assume the measured signal is the output signal which is the response about a input signal pass through an unknown linear time-invariant system. Once the system is described by a linear filter, the output signal is the convolution about input and the impulse response of the filter. The blind deconvolution is only use the measured signal of the unknown system, based on an optimization criterion and the assumption about source input signal such as independent and identically distributed non-Gaussian signal, remove the effects of convolution, extract or estimate the source signal.

1)*Mathematical Description*

Assume the measured signal, was generated by an unknown input signal passed by an unknown linear time-invariant filter:

$$x(k)=\sum_{i=-\infty}^{+\infty} a_i s(k-i)+n(k) \qquad (1)$$

Where $a_i, -\infty < i < +\infty$ is the impulse response sequence of convolution filter. Assume the source input signal $s(k)$ is a non-Gaussian sequence, the noise $n(k)$ is a zero-mean Gaussian random signal. They are statistically independent of each other.

The goal of the blind deconvolution task is to extract an estimate of the source signal sequence $s(k)$ from the measured sequence $x(k)$ using a linear filter of the form:

$$y(k)=\sum_{l=0}^{L} b_l(k)x(k-l) \qquad (2)$$

$$y(k)\approx cs(k-\Delta) \qquad (3)$$

Where $b_l(k), 0<l<L$ are the coefficients of the system and L is a filter length parameter. c is a scalar constant and Δ is appositive integer delay. Figure 1 indicates the structure of the blind deconvolution task.

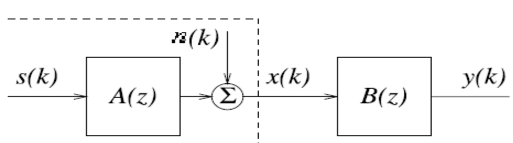

Figure 1：Block Diagram Of The Blind Deconvolution Task.

In this model, we assumed a causal finite-impulse-response filter for the deconvolution model. FIR models are ideal candidates for adaptive filters, as they are both computationally simple and bounded-input-bounded-output stable for bounded coefficients.

2)*Blind deconvolution algorithm*

Paper[13] extended H-J algorithm to the situation of time delay and convolution mixing. Paper[14] proposed the method about multi-channel blind deconvolution based on high-order cumulant and high-order spectrum. Blind system parameter identification and blind convolution can be executed at the same time by using recursive eigen decomposition. Paper[15] gave a adaptive method about how to separate convolution mixing signal blindly, by using 4 order cumulant or 4 order moment function.

Considering the relationship between blind convolution and blind signal separation, paper[16] proposed a blind convolution algorithm extended by fast fixed-point algorithm[17] based on contrast function. Based on the principle of max kurtosis, it doesn't need to select the step size parameter when calculating, and the convergence speed is fast. In this paper, we use this algorithm to deconvolution. The updates of this algorithm for N-sample block of complex-value data are as follow:

Step 1: Pre-whitening. Whitening the measured signal using a whitening filter.

$$v(k)=\sum_{i=0}^{M} p_i x(k-i) \qquad (4)$$

Where $p_i, 0<i<M$ are the coefficients of the filter, M is the order of the filter.

Step 2: Initialize the coefficients of the deconvolution filter $b_l(0)$ .Let vector $b(0)$ of norm 1.

Step 3: Set the number of iterations. Update the coefficients of $b_l(k)$.

Step 4 : The update algorithm is as follow:

$$y(k)=\sum_{l=0}^{L} b_l(k)v(k-l) \qquad (5)$$

$$b_l(k)=\left[\sum_{i=0}^{N} |y^2(k+i)|\, y(k+i)v^*(k+i-l)\right]-3b_l(k)$$

(6)

$$B_l(k)=\sum_{p=0}^{L} b_l(k)e^{-j2\pi pl/(L+1)} \qquad (7)$$

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$$B_l(k) = \frac{B_l(k)}{|B_l(k)|} \quad (8)$$

$$b_l(k+1) = \frac{1}{L+1}\sum_{p=0}^{L} B_p(k) e^{j2\pi pl/(L+1)} \quad (9)$$

Step 5: $k = k+1$,back to step 4,Calculating, until k equal to the number which had been set at step 3.

A remarkable property of this algorithm is that a very small number of iterations, usually 5-10, seem to be enough to obtain the maximal accuracy allowed by the sample data.

2.2. Spectral Kurtosis

Spectral kurtosis(SK) was introduced by Dwyer[18] at first, as a statistical tool which "can indicate not only non-Gaussian components in a signal, but also their locations in the frequency domain". Dwyer initially used it as a complement to the power spectral density, and demonstrated how it efficiently supplements the latter in problems concerned with the detection of transients in noisy signals. The basic thought of spectral kurtosis is: compute the kurtosis at each frequency, according the value to find out the transients signal which is hidden in the original signal, and determine the band of transients signal hidden. Antoni did a deep research about spectral kurtosis at paper[11,12], proposed a formalization of the SK by means of Wold-Cramer decomposition of "conditionally non-stationary" processes. It finally proposed a short-time Fourier-transform-based estimator of the SK which helps to link theoretical concepts with practical applications.

1) *Definition of the SK*

Considering the Wold-Cramer decomposition of non-stationary signal, define $Y(t)$ as the system response of signal $X(t)$, $Y(t)$ can be presented as follow:

$$Y(t) = \int_{-\infty}^{+\infty} e^{2\pi ft} H(t, f; \overline{w}) dX(f) \quad (10)$$

Where $H(t, f; \overline{w})$ is the time-varying transfer function of the system, which can be interpreted as the complex envelope of signal $Y(t)$ at frequency f. Because of it's a random function, the shape of the envelope is determined by time-varying variable $\overline{w}$.

We consider the case of transfer function is conditioned to a given outcome $\overline{w}$, the process has time-dependent statistics. Specifically, define the 2n-order instantaneous moment $S_{2nY}(t, f)$, which measures the strength of the energy of the complex envelope at time t and frequency f:

$$\begin{aligned} S_{2nY}(t, f) \quad & E\left\{|H(t, f) dX(f)|^{2n} | \overline{w}\right\} / df \\ & = |H(t, f)|^{2n} \; S_{2nX} \end{aligned} \quad (11)$$

With non-stationary processes it is necessary to investigate how the time-frequency structure behaves on the average, i.e. by ensemble averaging on many outcomes $\overline{w}$. So define spectral moments to convey the information as:

$$S_{2nY}(f) \quad E\left\{S_{2nY}(t, f)\right\} \quad (12)$$

Of particular interest for characterizing non-stationary processes, which has been shown are likely to be non-Gaussian, are the spectral cumulant. Indeed, spectral cumulant of order 2n more or equal than 4 have a interesting property of being non-zero for non-Gaussian processes. Define the fourth-order spectral cumulant as:

$$C_{4Y}(f) = S_{4Y}(f) - 2S_{2Y}^2(f), \quad f \neq 0 \quad (13)$$

It can be seen, the stronger the non-Gaussianity of signal, the greater the spectral cumulant. Therefore, the energy-normalized fourth-order spectral cumulant will give a measure of the peak of the probability density function of the process at frequency f. Define SK as:

$$K_Y(f) \quad \frac{C_{4Y}(f)}{S_{2Y}^2(f)} = \frac{S_{4Y}(f)}{S_{2Y}^2(f)} - 2, f \neq 0 \quad (14)$$

2) Application of SK at fault diagnosis in bearing

The vibration model of rolling element bearing can be presented as:

$$Z(t) = X(t) + N(t) \quad (15)$$

Where $Z(t)$ is the measured signal, $X(t)$ is the fault signal which is needed to detect, and $N(t)$ is the noise. $X(t)$ is the system structure resonance caused by instantaneous impact, so it can be presented like the model as follow:

$$X(t) = \sum_k X_k h(t - \tau_k) \quad (16)$$

Where $h(t)$ is the impulse response caused by single impact. X_k and τ_k present the amplitude and the time of occurrence of the impulse respectively.

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According the property proposed at paper[14], assume the noise follows the gauss distribution, the spectral kurtosis is:

$$K_Z(f)=\frac{K_X(f)}{\left[1+\rho(f)\right]^2}, f\neq 0 \qquad (17)$$

Where $\rho(f)=S_{2N}(f)/S_{2X}(f)$ is noise-signal ratio. $K_Z(f)$ is a function about frequency f ,it is approximation equal to $K_X(f)$ at the band where signal-noise ratio is high. Compute the SK value of the whole band we can find out the greatest kurtosis and the frequency band corresponding. It is useful for design a band-pass filter to fault diagnosis.

Antoni introduced the concept about kurtogram. Kurtogram is a function about frequency f and short-time Fourier transform window length N_w . The frequency and window length which maximize the SK, is the central frequency of the band f and the bandwidth $f_s\ 2/N_w$. Paper[19] proposed a fast kurtogram algorithm based on multi-resolution filter bank. And the concept about kurtogram in it is presented as a function relate to frequency f and bandwidth Δf . There is a dyad $\langle f,\Delta f\rangle$ maximize the SK, the kurtogram is used to present the SK value at plane $\langle f,\Delta f\rangle$. The computation in this paper is used by this algorithm.

3. EXPERIMENTAL RESULTS AND ANALYSIS

The bearing experiments in the study were carried out on vibration test system YVS-2, which has some faults in outer-race with cylindrical rolling bearing typed N203. Table 1 shows the parameter of N203. The rotation speed was 1750 round per minute, the sampling frequency was set to 32768Hz. Theoretically the fault feature frequency is 117.4Hz.

Table I: *Parameter Of Bearing N203.*

Number of roller	Roll diameter	Inside diameter
10	5.5mm	17mm
Outside diameter	Thickness	Pitch diameter
40mm	12mm	28.5mm

The sampling is showed as Figure 2, (a)(b) are time-domain waveform and the frequency spectrum respectively.

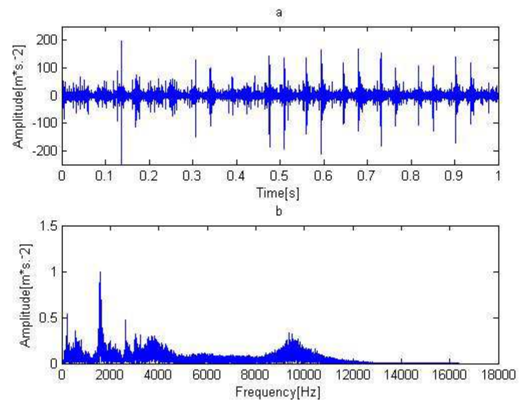

Figure 2：Time-domain Frequency-domain of the sampling.

Figure 3 and figure 4 show the fast kurtogram of the sampling and the spectrum of the signal which filtered by the best band-pass filter, respectively. As figure 3 shows, the amplitude of the spectrum, which band corresponding to the max kurtosis, is not clear. As figure 4 shows, the fault feature frequency is complex, which has several feature frequency and their harmonic, it is hard to recognize the fault frequency.

Figure 5 shows the time-domain waveform and frequency spectrum after blind deconvolution operation. Figure 6 shows the fast kurtogram of the signal after blind deconvolution operation. Figure 7 shows the spectrum of the signal which filtered by the best band-pass filter, after blind deconvolution operation. By compared figure 3 and figure 6, the value of max kurtosis increased significantly: the max kurtosis value is 147.3 in figure 3, and the max kurtosis value is 2578.3 in figure 6. As figure 7 shows, the fault feature frequency is 117.4Hz and its harmonic, which just right relate to the outer-race fault frequency.

4. CONCLUSION

This paper proposes an approach for convolution of multi-vibration sources and strong noise in rotating machinery vibration. The approach includes blind deconvolution and Spectral kurtosis method. Through the bearing failure experiment, the proposed approach could detect the fault feature frequency obviously, which shows good application potential for distinguishing the failure types in rotatory machine.

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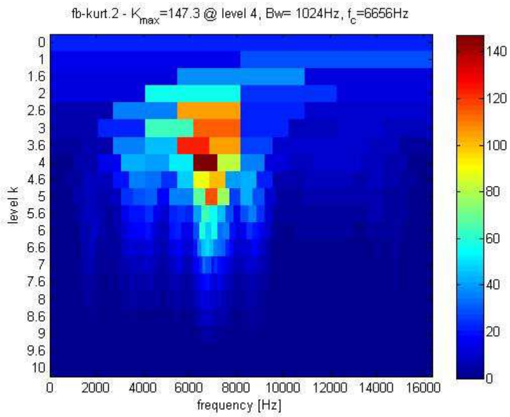

Figure 3：The kurtogram of the sampling.

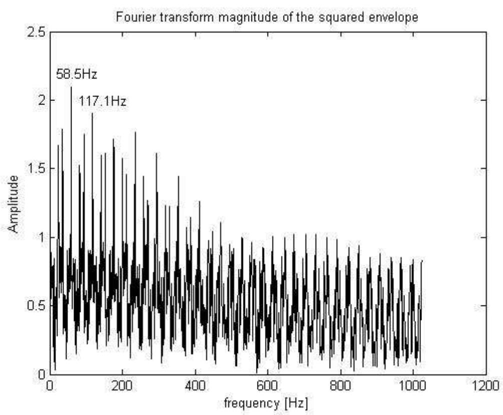

Figure 4：The spectrum of fault feature frequency with spectral kurtosis.

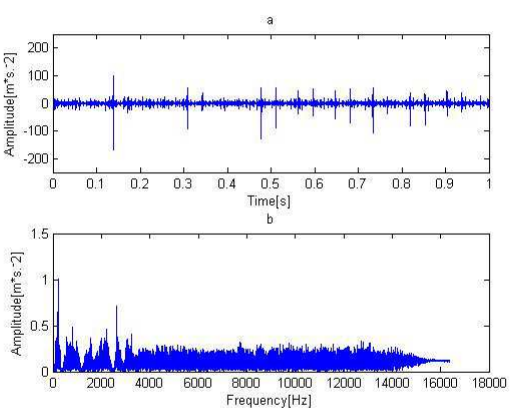

Figure 5：Time-domain waveform of the sampled data after deconvolution operation.

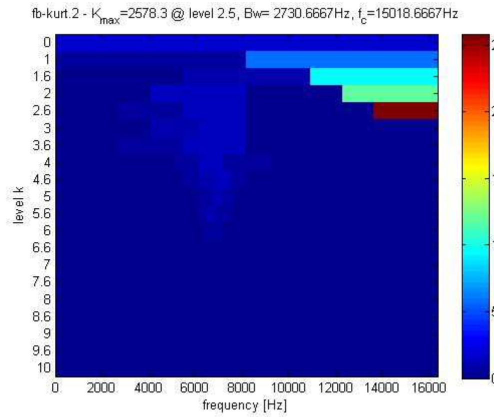

Figure 6：The kurtogram of the sampling after deconvolution operation.

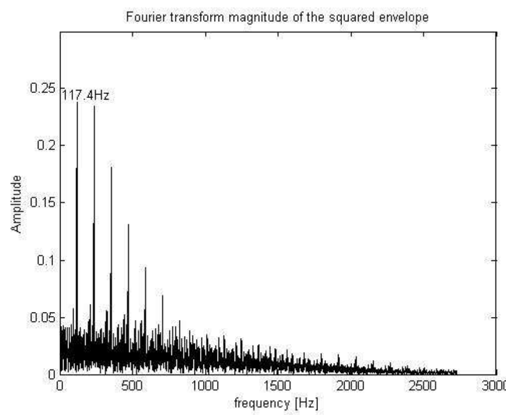

Figure 7：The spectrum of fault feature frequency with spectral kurtosis after deconvolution operation.

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