A Method for Incipient Fault Diagnosis of Roller Bearings Based on the Wavelet Transform Correlation Filter and Hilbert Transform

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Abstract: *Noise is the biggest obstacle that makes the incipient fault diagnosis results of roller bearings uncorrected; a new method for diagnosing incipient fault of roller bearings based on the Wavelet Transform Correlation Filter and Hilbert Transform was proposed. First, the weak fault information features are picked up from the roller bearings fault vibration signals by use of a de-noising characteristic of the Wavelet Transform Correlation Filter as the preprocessing of the Hilbert Envelope Analysis. Then, in order to get fault features frequency, de-noised wavelet coefficients of high scales which represent high frequency signal were analyzed by Hilbert Envelope Spectrum Analysis. The simulation signals and diagnosing examples analysis results reveal that the proposed method is more effective than the method of direct wavelet coefficients-Hilbert Transform in de-noising and clarifying roller bearing incipient fault.*
Key words: wavelet correlation Filter, Hilbert transform, envelope spectrum, fault diagnosis, roller bearings

1 Introduction

Roller bearings are frequently applied components in the vast majority of rotating machines. Their running quality influences the working performance of equipment. At present, the generally used methods for diagnosing roller bearing fault include FFT spectrum analysis and high frequency demodulation analysis, but the two methods are deficient. The reasons are: (1) bearing fault vibration signals usually have unstable characteristics; (2) the feature information of roller bearing incipient fault is weak and the working condition is full of noise; feature information is inundated with noise and difficulty identified. So how to pick up fault feature information and how to increase signal-to-noise ratio are the key technologies for diagnosing roller bearing incipient fault.

Wavelet analysis came forth in the 1980s. Since then, people began to use wavelet analysis to deal with vibration signals and achieved some favorable effects[1-3]. Almost all methods use Wavelet Transform (WT) or Wavelet Pocket Translation (WPT) to pick up fault characteristics directly, which were not ideal when the working condition is full of strong noise. The reason is that fault signals are inundated with noise in each frequency channel. The Wavelet Transform Correlation Filter (WTCF) is based on the fact that sharp edges have large signals over many wavelet scales and noise

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will die out swiftly with scale; the direct spatial correlation of wavelet coefficients at several adjacent scales sharpens and enhances edges and significant features while suppressing noise and small sharp features; edges and significant features can be obtained from the noise, and noise is removed based on threshold inspection; signal-to-noise ratio of wavelet coefficients of WTCF is much higher than that of wavelet coefficients of WT. In this paper, a new method of diagnosing incipient fault of roller bearings based on WTCF and Hilbert Transform is proposed. First, the weak fault information features are picked up from the roller bearing fault vibration signals by use of a de-noising characteristic of the WTCF as the preprocessing of the Hilbert Envelope Analysis. Then, in order to get fault feature frequency, de-noised wavelet coefficients of high scales which represent a high frequency signal is analyzed by the Hilbert Envelope Spectrum. The simulation signals and diagnosing examples analysis results reveal that the proposed method is more effective than the method of direct wavelet coefficients-Hilbert Transform in de-noising and clarifying roller bearing incipient fault.

2 Wavelet transform correlation filter

The de-noising idea of the Wavelet Transform Correlation Filter(WTCF)[4] is based on the fact that sharp edges have large signals over many wavelet scales and noise will die out swiftly with scale; the direct spatial correlation of wavelet coefficients at several adjacent scales sharpens and enhances edges and significant features while suppressing noise and small sharp features; edges and significant features can be obtained from the noise and noise is removed based on threshold inspection. Signal-to-noise ratio of wavelet coefficients of WTCF is much higher than that of wavelet coefficients of WT. The WTCF have easily implemented and robust characteristics, and it can be as a signal processing tool applied to pick up incipient fault features of mechanical equipment. We are using the direct spatial correlation $Corr_l(m, n)$ of wavelet transform contents at several adjacent scales to accurately detect the locations of edges or other significant features.

$$Corr_l(m,n) = \prod_{i=0}^{l-1} Y(m+i,n), \qquad n = 1,2\cdots,N \tag{1}$$

Where N is the point number of a discrete signal, n is the translation index, m is the scale index, Y denotes the wavelet transform data[4], l is the number of scales involved in the direct multiplication, $m < M - l + 1$, and M is the total number at scales. Usually, we select $l = 2$. The presence of edges or other significant features in a localized region of the signal allows the noisy background to be removed. The direct spatial correlation of edge-detection data over several scales sharpens and enhances major edges while suppressing noise and small sharp features. In this paper, the proposed algorithm makes use of the correlation characteristics to pick up significant features from the noise.

The algorithm is described briefly as follows: the filtered data is referred to as Yf, the initializations of all elements are zero.

(1) Compute the correlation $Corr_2(m, n)$ for every wavelet scale m to obtain enhanced significant features and suppressed noise.

(2) Rescale the power of $\{Corr_2(m, n)\}$ to that of $\{Y(m, n)\}$ and get $\{\text{New } Corr_2(m, n)\}$

$$\text{New } Corr_2(m,n) = Corr_2(m,n)\sqrt{\frac{PY(m)}{PCorr(m)}} \tag{2}$$

Where
$$PY(m) = \sum_{n} Y(m,n)^2 \tag{3}$$
$$PCorr_2(m) = \sum_{n} Corr_2(m,n)^2 \tag{4}$$
$PY(m)$ is the mth scale wavelet coefficients and $PCorr_2(m)$ is the mth power of $Corr_2(m, n)$.

(3) If $|New\ Corr_2(m, n)| \geq |Y(m, n)|$, we accept the point as an edge. Pass $Y(m, n)$ to Yf, and reset $Y(m, n)$ and $Corr_2(m, n)$ to 0. Otherwise, we assume $Y(m, n)$ is produced by noise and then retain $Y(m, n)$ and $Corr_2(m, n)$.

(4) Return to (1), repeat (2) and (3) until the power of $Y(m, n)$ is nearly equal to the threshold ratio $th(m)$ which is correlated with some reference noise power at the mth wavelet scale.

This procedure of power normalization, data value comparison, and edge information extraction can be iterated many times until the power of un-extracted data points in $Y(m, n)$ is nearly equal to some reference noise power at the mth wavelet scale[5,6].

On the start of the process, it is necessary to estimate the reference noise. In fact, we find that too much noise will be extracted as edges through experiment analysis, to avoid this, we multiply $|Y(m, n)|$ by a weight $\lambda(m) \geq 1$ and impose that only when $|New\ Corr_2(m, n)| \geq \lambda(m)\ |Y(m, n)|$ can we extract $Y(m, n)$ as edges. The detailed content of reference noise estimation refers to literature [6].

3 The method of diagnosing incipient fault of roller bearings based on the wavelet transform correlation filter and Hilbert transform

High frequency scales wavelet coefficients acquired by WTCF de-noising can not only divide mutated vibration signals of roller bearing fault, but more important, it keeps the time information, which reflects the repetitive frequency and their changing rules and includes roller bearing fault information[7]. In order to get fault information effectively, it needs to do a Hilbert Transform on high frequency scales wavelet coefficients, and then to do Envelope Spectrum Analysis.

If $d(t)$ is the wavelet coefficient of one scale, and the hilbert Transform of $d(t)$ is
$$\hat{d}(t) = H\{d(t)\} = \frac{1}{\pi}\int_{-\infty}^{+\infty} \frac{d(\tau)}{t-\tau}\mathrm{d}t \tag{5}$$
And the envelope signal of wavelet coefficient $d(t)$ is
$$b(t) = \sqrt{d^2(t) + \hat{d}^2(t)} \tag{6}$$
All fault characteristic frequencies of roller bearings are low compared with the sample frequency; low frequency spectrum analysis on Hilbert Envelope Signals of de-noised wavelet coefficients is necessary to improve the envelope spectrum differentiate rate. When directly do low frequency spectrum analysis on discrete vibration signals $x(n)$, $x(n)$ is necessarily re-sampled. For example, in order to process 8 times spectrum analysis, firstly, a new data sequence $z(m)$ is reformed by the data point which is sampled from $x(n)$ every other 8 points, and then frequency analysis of $z(m)$ is done. The relation between $z(m)$ and $x(n)$ is
$$z(m) = x(8m) \quad m = 1,2,\cdots,M \tag{7}$$
When we do a low frequency spectrum analysis on the Hilbert Envelope Signal of wavelet coefficient $d(t)$, it is necessary to resample wavelet coefficient $d(t)$, but the resample rule is different from

the aforementioned rule of discrete vibration signal resample. Because every time a decomposed result of wavelet transform is obtained by re-sampling one point from two points, the sample frequency decreases by one half. Furthermore, resample frequency will decrease by the rate of 2^{-j} along with the augment of scale j, so when we do a spectrum analysis on the Hilbert Envelope Signal of every scale wavelet coefficient, the resample interval needs to decrease by the rate of 2^{-j} along with the augment of scale j. For example, when we do 8 times spectrum analysis on the Hilbert Envelope Signal of wavelet coefficient $d_1(t)$, the resample interval is 4 points in the d_1 layer. In this paper, the Hilbert Envelope Signal of high frequency scales wavelet coefficient $d_1(t)$, which is de-noised by WTCF, is re-sampled based on the aforementioned resample rule, and then we do a power spectrum analysis.

The process for diagnosing incipient fault of roller bearings based on WTCF and Hilbert Transform is divided into two phases (shown in Figure 1): (1) Based on the de-noising idea of Wavelet Transform Correlation Filter (WTCF), the direct spatial correlation of wavelet coefficients at several adjacent scales sharpens and enhances edges and significant features while suppressing noise and small sharp features. Edges and significant features can be obtained from the noise and noise is removed based on threshold inspection, Signal-to-Noise of wavelet coefficients of WTCF is much higher than that of the wavelet coefficients of WT.

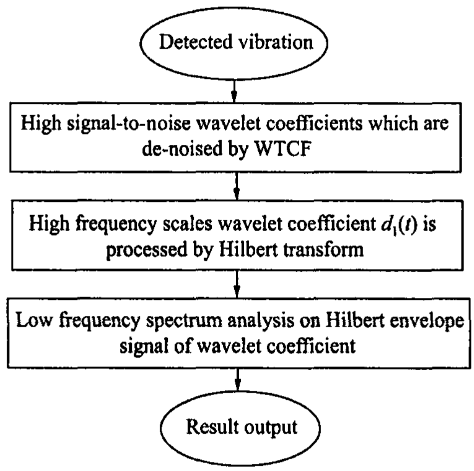


Figure 1 The flow chart of fault diagnosis method based on WTCF and Hilbert transform

(2) High frequency scales wavelet coefficient $d_1(t)$, which is de-noised by WTCF, is processed by Hilbert Transform Envelope Spectrum Analysis, and then we can get the feature frequency of the fault.

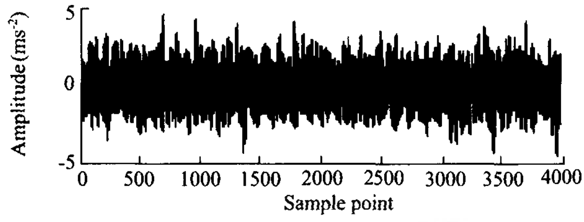
4 Simulation analysis

The analyzed data are obtained as follows: (1) The impulse train of 120 Hz imitates passing vibration, which has a single fault point; (2) A single harmonic of 3000 Hz with an exponential decay imitates the natural frequency excited is added; (3) Two low component frequencies of 20 Hz and 130 Hz imitate factors such as unbalance, misalignment, mechanical looseness etc, are added; (4) Strong white Gaussian noise is added to imitate environmental disturbances. Sample frequency is 16384 Hz[8]

Figure 2 (a) presents the original vibration signal and the fault frequency is 120 Hz. The fault signal is inundated with noise. Figure 2 (b) presents the envelope spectrum analysis of a direct wavelet coefficient-Hilbert Transform, there is no means to judge whether the fault exists. Figure 2 (c) shows the envelope spectrum analysis of the WTCF-Hilbert Transform; the fault frequency 120 Hz and its higher harmonics are clearly observed.

5 Analysis of diagnosis example

In order to validate the validity and practicability of the proposed method based on WTCF and Hilbert Transform in diagnosing the incipient fault of a roller bearing, several main faults of roller bearings test-bed are analyzed. Tester and test data come from USA Case Western Reserve University electric engineering lab[9]. In the tester, three-phase induction motors whose power is 1.5 kW is joined with a power meter and a torque sensor by one self-calibration coupling, to drive fans. Data is gathered by the vibration acceleration sensor which is a vertically fixed shell of the supporting bearing of the induction motors export-shaft. Simulating three running states of roller bearings: (1) outer race slight fault; (2) inner race slight fault; (3) ball slight fault, and the defect size is 0.18 mm. In the three running states, the work frequency of bearing f_i is 30 Hz, outer race fault feature frequency f_{outer} is 91.6 Hz, inner race fault feature frequency f_{inner} is 148.4 Hz, and ball fault feature frequency f_{ball} is 119.6 Hz. Sampling point is 4096, sampling frequency is 12 kHz.



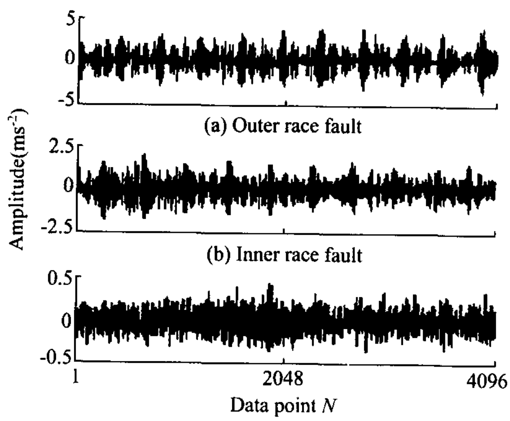
(a) Original vibration signal

(b) The envelope spectrum analysis of direct wavelet coefficient-Hilbert Transform

(c) The envelope spectrum analysis of WTCF-Hilbert Transform

Figure 2 Simulation vibration signal analysis

Time field wave shape of three incipient weak faults are shown in Figure 3; we know from Figure 3 that the incipient fault signal is very weak and basically inundated with noise; it is difficult to distinguish the existence of fault and fault feature frequency, especially as the ball fault is completely inundated with noise.



(a) Outer race fault

(b) Inner race fault

(c) Ball fault

Figure 3 Time field wave shape of original vibration signal

Figure 4 shows the envelope spectrum analysis of the WTCF-Hilbert Transform.

When there is outer race fault, Figure 4 (a) presents the envelope spectrum analysis of the WTCF-Hilbert Transform, there are distinct spectrum lines in the outer race fault feature frequency f_{outer} (91.6 Hz) and its high frequencies.

When there is inner race fault, Figure 4 (b) illustrates the envelope spectrum analysis of the WTCF-

Hilbert Transform; there are distinct spectrum lines in the inner race fault feature f_{inner} (148.4 Hz) and work frequency f_i (30 Hz) of the bearings.

When there is ball fault, Figure 4 (c) shows the envelope spectrum analysis of the WTCF-Hilbert Transform; there are distinct spectrum lines in the ball fault feature f_{ball} (119.6 Hz).

Figure 5 shows the envelope spectrum analysis of direct wavelet coefficient-Hilbert Transform, from Figure 5 (a) and (b), we know that when there are outer race faults and inner race faults, the method can diagnose the existence of fault, but the amplitude of fault frequency is not distinct, and the diagnosis effect is not good, when there is ball fault; the envelope spectrum analysis of direct wavelet coefficient-Hilbert Transform can not diagnose the existence of fault as shown in Figure 5 (c).

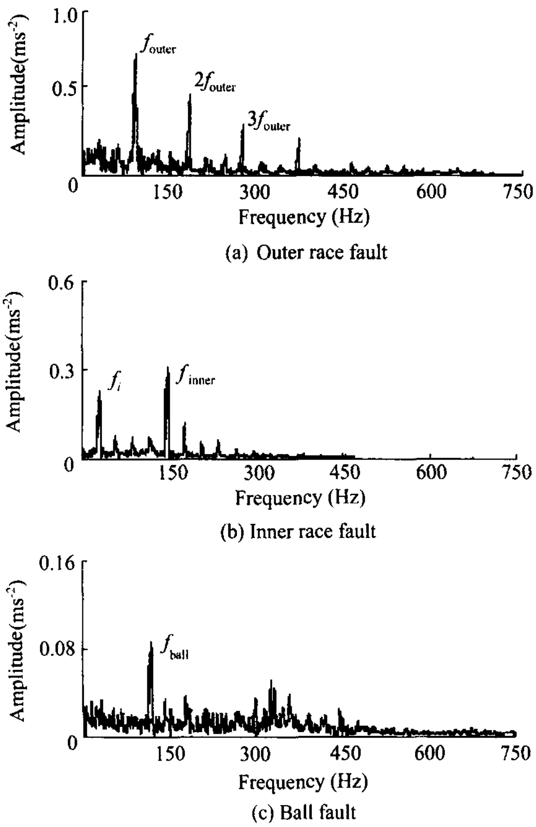


Figure 4 The envelope spectrum analysis of WTCF-Hilbert Transform

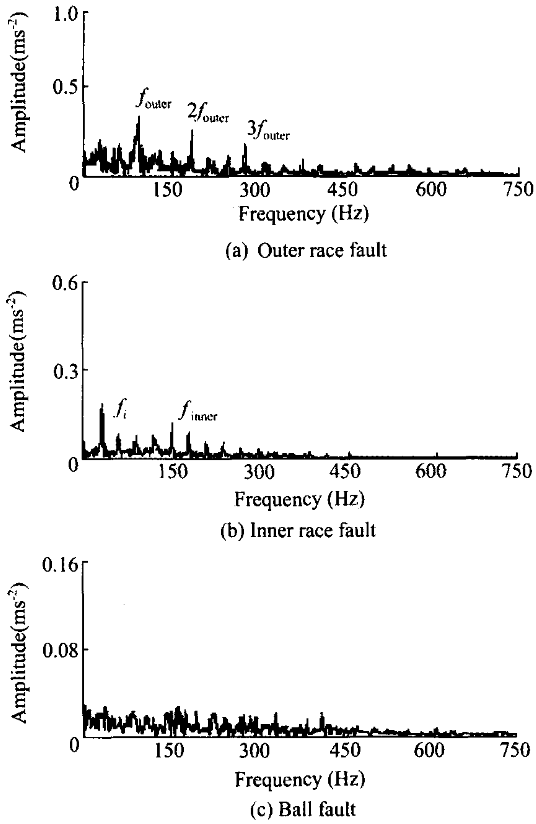


Figure 5 The envelope spectrum analysis of direct wavelet coefficient-Hilbert Transform

6 Conclusions

When there are incipient faults of roller bearings, very weak fault feature signals are often inundated with vibration signals and noise, the de-noising of the vibration signal is a main approach of diagnosing incipient fault of roller bearings. In this paper, an approach of diagnosing incipient fault of roller bearings is proposed based on the Wavelet Transform Correlation Filter and Hilbert Transform. First, the weak fault information features are picked up from the roller bearings fault vibration signals by use of a de-noising characteristic of the Wavelet Correlation Filter as the preprocessing of the Hilbert Envelope Analysis; Then, in order to get fault features frequency, de-noised wavelet coefficients of high scales which represent a high frequency signal is analyzed by the Hilbert Envelope Spectrum. The simulation signals and diagnosing examples analysis results reveal that the proposed method is more effective than the method of direct wavelet coefficients-Hilbert Transform in de-noising and clarifying incipient fault.

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Brief Biographies

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