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An Adaptive Decomposition Algorithm of the Mixed Signals for Bearing Faults Characteristics Extraction

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Abstract: Rolling-element bearing faults are the most frequent faults in induction machines. This paper proposes a bearing fault characteristics extraction and fault diagnosis algorithm which is named as the SWPHT algorithm. Firstly, stationary wavelet packet transform was used to pretreat the signal and thus the signal was decomposed into low- and high-frequency sub-bands. Subsequently, Hilbert transform was used to obtain the instantaneous frequency and instantaneous amplitude of the low- and high-frequency sub-bands. Finally, the proposed SWPHT algorithm adaptively selects the path of signal decomposition and extracting the characteristic frequency components for fault diagnosis. The simulations show that the SWPHT algorithm provides sufficient frequency-amplitude fault information with the less computational workloads and data storage spaces. The algorithm also has a good anti-noise performance.

Key words: Mixed signal, adaptive analysis, stationary wavelet packet transform, Hilbert transform, characteristics extraction, fault diagnosis

INTRODUCTION

Induction motors are now widely used in all kinds of industrial applications due to their simple construction, high reliability and the availability of power converters using efficient control strategies. However, the failure of the electrical drive would decrease the productivity, reliability and safety of the entire installation. According to an IEEE motor reliability study by Blodt *et al.* (2008), rolling-element bearing faults are the most frequent faults in induction machines (41%). When a rolling-element bearing fails, the local damage components under high frequency vibration will stir up the characteristic frequency vibration of the bearing system. As the amplitude of the high-frequency vibration is modulated by the pulse excitation force, the vibration signal of rolling-element bearing failure has the performance of non-stationary characteristics. The vibration signal contains the fault characteristic frequency of a family of harmonics which are the Fourier components of periodic signals. Thus their phases are interconnected. And there is a quadratic phase coupled between the local damage vibration signals. Therefore, the bearing failure vibration signal is a nonlinear, non-stationary and non-Gaussian signal (Kang *et al.*, 2007). Hilbert-Huang Transform (HHT) has initially been verified as a new analytical method for nonlinear and non-stationary time series in study of Huang *et al.* (1998), Wu and Huang (2004) and Flandrin *et al.* (2004). HHT is a self-adaptive algorithm for signals and also able to gather the local time-frequency

performance of the signals. However, its core algorithm, Empirical Mode Decomposition (EMD) algorithm, still has some defects (Wang *et al.*, 2010). Olhede and Walden (2004, 2005) proposed a new method which is Wavelet Packet Transform (WPT), to get the narrow-band decomposition of signals. Olhede's method not only overcomes the EMD's defects but also maintains a good time-frequency spectral resolution.

This study uses an integrated algorithm named as Stationary Wavelet Packet and Hilbert Transform (SWPHT) algorithm to decompose the bearing vibration signal and calculate the instantaneous frequency-amplitude information of the extracted narrow-band vibration components. According to bearing's fault characteristic frequency, the algorithm adaptively selects the path of stationary wavelet packet decomposition for signals. Then based on the preset frequency-amplitude criteria, the single components and low-energy components can be recognized. When a bearing fails, the corresponding characteristic frequency components can be picked out for fault diagnosis.

STATIONARY WAVELET PACKET TRANSFORM

Stationary wavelet packet transform inherits the traditional wavelet packet transform. Without the under sampling process, a stationary wavelet packet transform avoids the inherent defects of the traditional wavelet

packet transform in lower time-resolved. It not only improves the frequency resolution but also maintains a temporal resolution.

For any continuous time signal $x(t)$, the discrete stationary wavelet packet coefficient at level i and sub-band k is:

$$w_{i,k}(t) = \sum_{\tau=0}^{L-1} f_{i,k}(\tau) x[(t-\tau) \bmod N] \quad (1)$$

where, $\{f_{i,k}(\tau)\}$ is the stationary wavelet packet filter at level i and sub-band k . Thus the component at level i and sub-band k , with the number of 2^{i+k-1} , is:

$$d_{i,k}(t) = \sum_{\tau=0}^{L-1} f_{i,k}(\tau) w_{i,k}[(t-\tau) \bmod N] \quad (2)$$

ROLLING-ELEMENT BEARING FAULT

Bearing fault types: This study considers rolling-element bearings with a geometry shown in Fig. 1. The bearing consists mainly of the outer and inner raceway, the balls and the cage which assures equidistance between the balls. The number of balls is defined as N_b , their diameter as D_b . The pitch diameter or diameter of the cage is designated D_c . The point of contact between a ball and the raceway is characterized by the contact angle β .

The different faults occurring in a rolling-element bearing can be classified according to the affected element: outer raceway defect, inner raceway defect and ball defect.

A fault could be imagined as a small hole, a pit or a missing piece of material on the corresponding element.

Fault characteristic frequencies: With each type of bearing fault, a characteristic frequency can be associated. This frequency is equivalent to the periodicity by which an anomaly appears due to the existence of the fault. The characteristic frequencies are functions of the

bearing geometry and the mechanical rotor frequency f_r . A detailed calculation of these frequencies can be found by Li *et al.* (2000). Their expressions for the above three considered fault types are given by:

- Outer raceway:

$$f_o = \frac{N_b}{2} \left(1 - \frac{D_b}{D_c} \cos \beta \right) f_r \quad (3)$$

- Inner raceway:

$$f_i = \frac{N_b}{2} \left(1 + \frac{D_b}{D_c} \cos \beta \right) f_r \quad (4)$$

- Ball:

$$f_b = \frac{D_c}{D_b} \left(1 - \frac{D_b^2}{D_c^2} \cos^2 \beta \right) f_r \quad (5)$$

SWPHT ALGORITHM

This algorithm chooses stationary wavelet packet decomposition as the pretreatment of Hilbert transform and the extractor of characteristic frequency components. Through one-level stationary wavelet packet transform, signal will be decomposed into the high- and low-frequency narrow-band components. Then Hilbert transform was used to calculate the instantaneous frequency and instantaneous amplitude of the high- and low-frequency narrow-band signals. Thus the single-component signal (named as type A component) and low-energy component (named as type B component) can be extracted based on the preset frequency and amplitude criteria. According the bearing defect characteristic frequencies, this method can adaptively choose the decomposition paths and levels of the stationary wavelet packet decomposition until all characteristic components have been extracted.

Component extraction criteria: As the one-level stationary wavelet packet decomposition is applied on signal level by level. The single component (named as type A component) and the low-energy component (named as type B component) can be extracted by calculating the instantaneous frequency and instantaneous amplitude of sub-bands.

For the time series $x(t)$, the instantaneous frequency and instantaneous amplitude of the sub-band $d_{i,k}(t)$ are $f_{i,k}(t)$ and $a_{i,k}(t)$, respectively, where $t = 1, 2, \dots, N$.

The extraction conditions of type A component is:

$$\frac{1}{N} \cdot \sum_{t=1}^N [f_{i,k}(t) - \bar{f}_{i,k}]^2 \leq K_A \quad (6)$$

where:

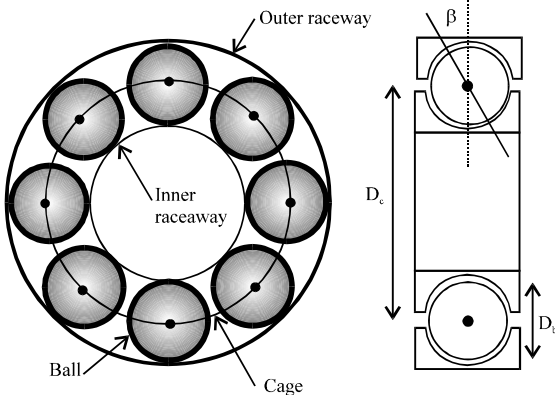


Fig. 1: Geometry of a rolling-element bearing

$$\bar{f}_{i,k} = \frac{1}{N} \cdot \sum_{i=1}^N f_{i,k}(t)$$

is the mean frequency and K_A is the preset threshold. This component can be considered as the characteristic frequency component.

The extraction conditions of the type B component are:

$$\frac{1}{N} \sum_{i=1}^N |a_{i,k}(t)|^2 \leq K_B \quad (7)$$

where, K_B is the preset energy threshold. This component can be considered as noise.

Bearing fault diagnosis: According to the affected element, a rolling-element bearing has three main faults including the outer raceway fault, the inner raceway fault and the rolling ball fault. With each type of bearing fault, a characteristic frequency can be associated. This frequency is equivalent to the periodicity by which an anomaly appears due to the existence of the fault. The characteristic frequencies are functions of the bearing geometry and the mechanical rotor frequency. The bearing fault diagnosis flow is designed as shown in Fig. 2. The fault types can be decided by the mean frequency of the characteristic frequency component which is extracted from the vibration signal by SWPHT algorithm.

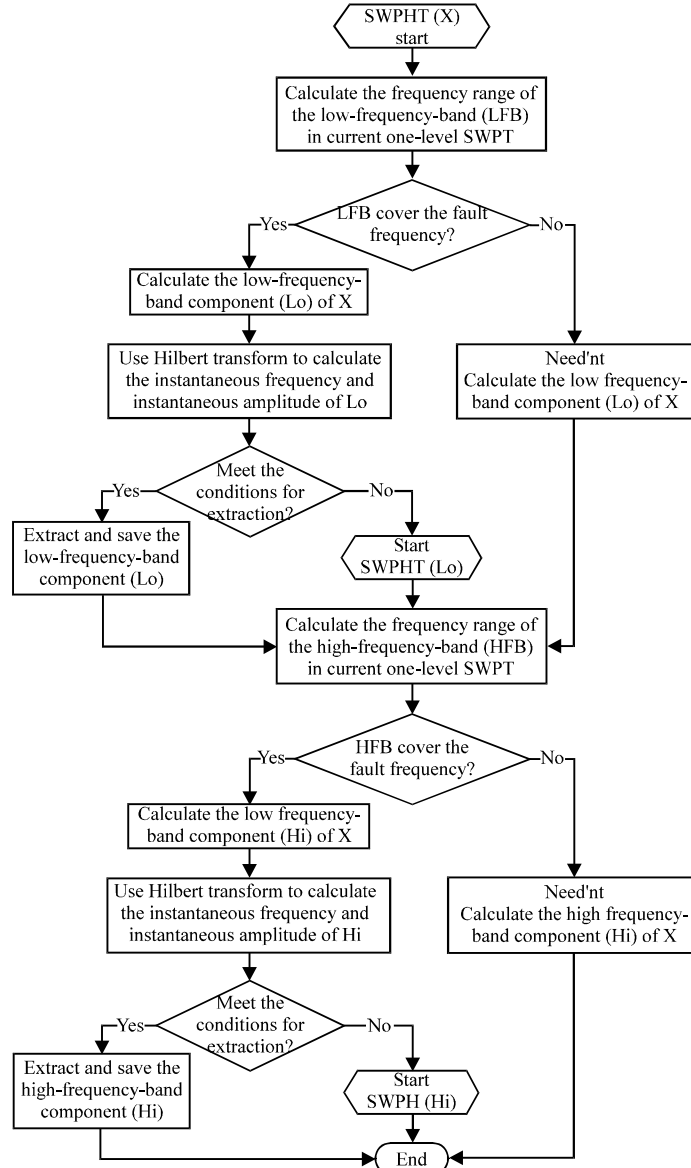


Fig. 2: SWPHT algorithm

ALGORITHM TEST

The expression of the mixed signal is assumed as:

$$f(t) = A_1 \sin(2\pi f_1 t) + A_2 \sin(2\pi f_2 t) + A_3 \sin(2\pi f_3 t) + n(t) \quad (8)$$

where, f_1 , f_2 and f_3 are the frequency of the three components while A_1 , A_2 and A_3 are the Amplitude. $n(t)$ is the added noise and the Signal-to-Noise Ratio (SNR) is calculated by:

$$SNR = 20 \log_{10} \frac{P_f}{P_n} \quad (9)$$

where, P_f is the power of the mixed signal and P_n is the power of the added noise.

The results of the algorithm testing are shown in Fig. 3, where, $f_1 = 5$ Hz, $f_2 = 50$ Hz, $f_3 = 500$ Hz, $A_1 = A_2 = A_3 = 1$ and SNR = 16 dB. The results show that the proposed algorithm can extract the characteristic frequency components and has a good anti-noise performance too.

EXPERIMENTAL RESULTS

Bearing fault signal: As shown in Fig. 4, the bearing fault test platform consists of a 2 HP motor, a torque transducer/encoder, a dynamometer and control electronics (not shown). The test bearings support the motor shaft. Single point faults were introduced to the test bearings using electro-discharge machining. Vibration data were collected using

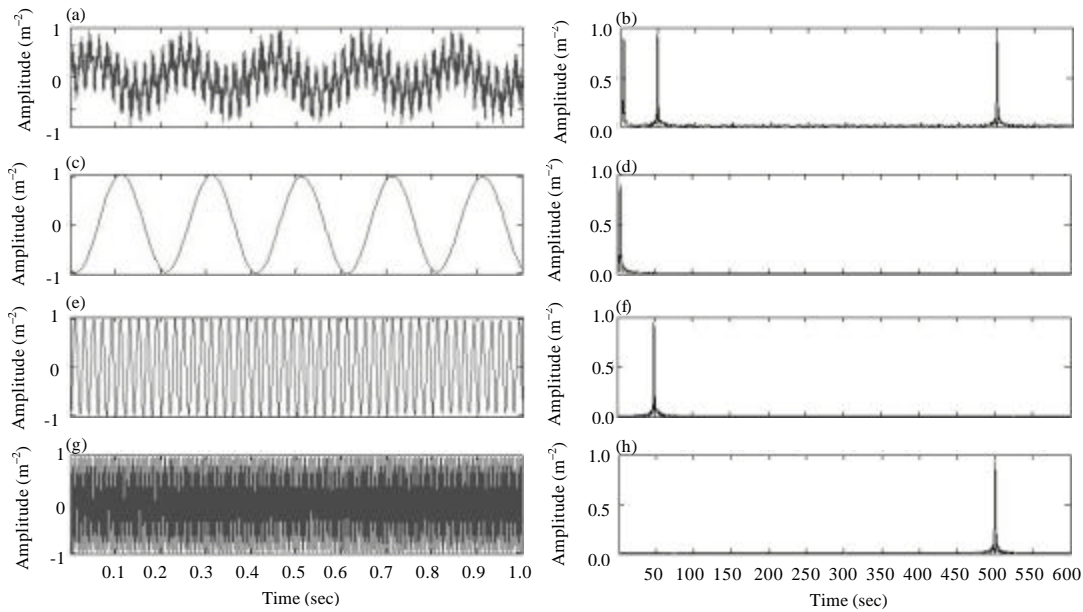


Fig. 3(a-h): Adaptive decomposition results of the mixed signal (a) The mixed signal, (b) Single-sided amplitude spectrum of the mixed signal, (c-d) Waveform and single-sided amplitude spectrum of the 5 Hz signal, (e-f) Waveform and single-sided amplitude spectrum of the 50 Hz signal and (g-h) Waveform and single-sided amplitude spectrum of the 500 Hz signal containing noise (SNR = 16 dB)

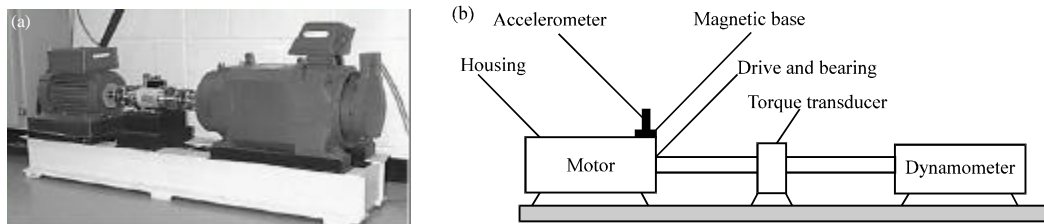


Fig. 4(a-b): Bearing fault test (a) Experiment platform and (b) Schematic diagram of the experimental platform

accelerometers which were attached to the housing with magnetic bases. Vibration signals were collected using a 16 channel DAT recorder at 12,000 samples per second. This study uses the outer raceway defect signal for bearing fault detection. Figure 5a is the bearing vibration signal waveform. From its amplitude spectrum shown in Fig. 5b, the characteristic frequency of outer raceway fault which is 147.76 Hz, can be found.

Bearing fault diagnosis results: The signal decomposition and bearing fault diagnosis results are shown in Fig. 5. Figure 5c is the outer raceway fault component which is extracted from the vibration signal waveform as shown in Fig. 5a. The mean value of the instantaneous frequency is 147.72 Hz, as shown in Fig. 5e. This method has less computational workloads and data storage spaces than the general signal decomposition algorithm. The results are shown in Fig. 6.

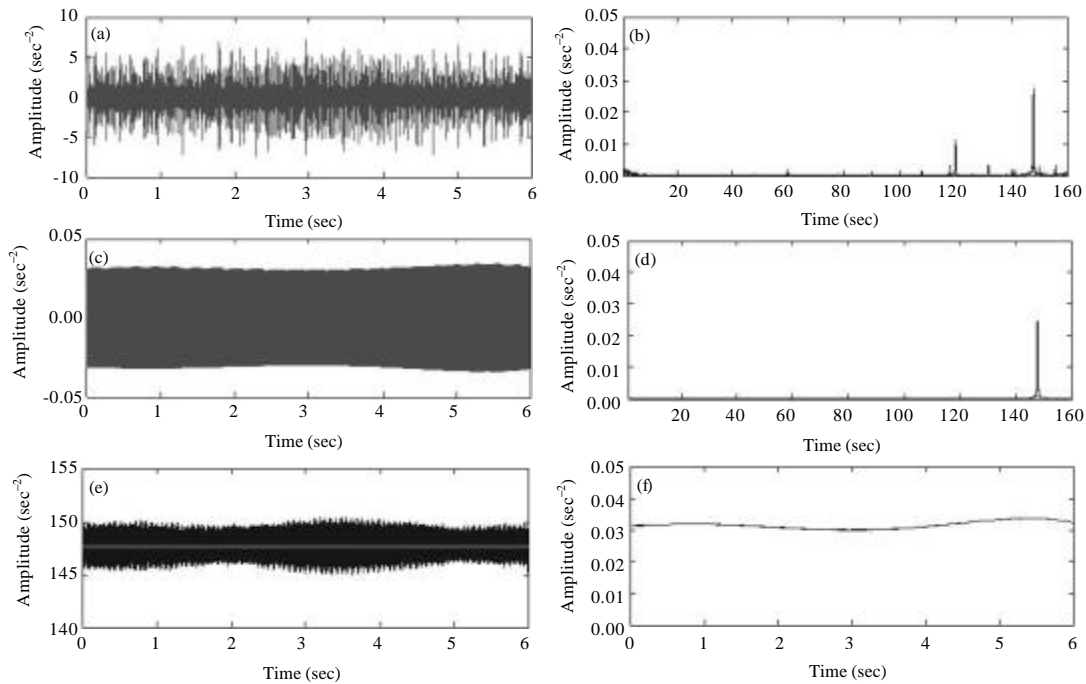


Fig. 5(a-f): Results of characteristics extraction (a) The vibration signal waveform, (b) Single-sided amplitude spectrum of vibration signal, (c) Outer ring fault characteristic frequency component, (d) Single-sided amplitude spectrum of fault component, (e) The instantaneous frequency of faulty component and (f) The instantaneous amplitude of fault component

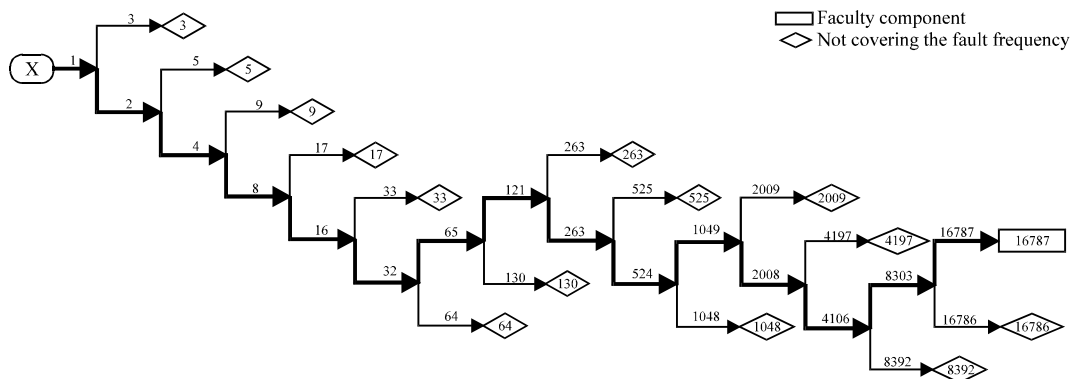


Fig. 6: Stationary wavelet packet decomposition tree

CONCLUSION

This study proposed an adaptive method which is named as SWPHT algorithm, to extract the characteristic frequency components of the mixed signals. The effectiveness of the proposed algorithm is tested in the extraction of the nonlinear and non-stationary fault components of the bearing vibration signals. According to the experimental results, the proposed method can adaptively choose the decomposition paths of the bearing vibration signals and pick out the corresponding characteristic frequency components for fault diagnosis. The simulations show that the SWPHT algorithm provides sufficient frequency-amplitude fault information with the less computational workloads and data storage spaces. The algorithm also has a good anti-noise performance.

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