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Bearing fault signature extraction under time-varying speed conditions via Oscillatory Behavior-based Signal Decomposition

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Abstract— Oscillatory Behavior-based Signal Decomposition (OBSD) is a new technique which decomposes a signal according to oscillatory behavior, instead of frequency bands. It has been used for bearing fault signature extraction under constant speed conditions, where the bearing fault-induced vibration signal can be regarded as a low oscillatory component and the interference can be regarded as a high oscillatory component. However, its effectiveness for bearing fault signature extraction under time-varying speed conditions has not been evaluated. Theoretically, the OBSD is a frequency-independent method and should thus be effective under time-varying speed conditions. In this paper, the performance of the OBSD for bearing fault signature extraction under time-varying speed conditions is examined. The results show that the OBSD can be effectively utilized to extract the bearing fault signature under time-varying speed conditions.

Keywords- Bearing fault feature extraction; Time-varying speed; Oscillatory behavior-based signal decomposition

I. INTRODUCTION

Bearing fault diagnosis is a useful means to prevent early bearing faults from developing into severe faults, which may lead to machine breakdown. Bearing faults can be detected and diagnosed by observing the Fault Characteristic Frequency (FCF) and its harmonics in the frequency domain of the vibration signal [1]. Each type of fault has a specific FCF, which is proportional to the rotational speed [2]. However, the collected bearing vibration signal is often contaminated by random noise and interferences transmitted from other sources, such as gears. Therefore, bearing fault signature extraction is an important step to insure the accuracy of bearing fault diagnosis.

Band-pass filtering is a commonly used method to extract the bearing fault signature [3]–[5]. The essence of this method is to remove the interference signal by using band-pass filters. However, the effectiveness of band-pass filters can be suppressed if the bearing fault-induced signal and the inference signal have similar frequency features. Additionally, in reality bearings are often operated under time-varying speed conditions which may also reduce the effectiveness of band-pass filters. Therefore, it is necessary to implement frequency-independent methods to extract bearing fault signatures under time-varying speed conditions.

Oscillatory Behavior-based Signal Decomposition (OBSD) is a newly developed method which can be used to decompose a signal according to oscillatory behavior, instead of frequency bands [6]. It can be implemented to extract the bearing fault signature from the signal contaminated by interferences since the bearing fault-induced signal can be considered as a low oscillatory component and the inference signal can be considered as a high oscillatory component. Its effectiveness for bearing fault signature extraction under constant speed condition has been validated [7]. However, the performance of the OBSD for bearing fault signature extraction under time-varying speed conditions has not been examined. Theoretically, the OBSD should be still effective under time-varying speed conditions since it is frequency-independent.

In this paper, the performance of the OBSD for bearing fault signature extraction under time-varying speed conditions is investigated. Signals collected from experimental apparatus are used to examine the effectiveness of the OBSD.

II. OSCILLATORY BEHAVIOR-BASED SIGNAL DECOMPOSITION

The essence of the OBSD method is utilizing two sets of wavelets with two different oscillatory behaviors to estimate a given signal [6]. The signal is decomposed into a low oscillatory component and a high oscillatory component by the OBSD. Therefore, the OBSD method can be used to extract the bearing fault signature from a signal obscured by interferences.

Compared to frequency or scale based methods for interference removal, the OBSD is superior since the signal decomposition is based on oscillatory behavior instead of frequencies. A Q-factor, defined as the ratio of the center frequency to the bandwidth of the frequency response, is used to describe the oscillatory behavior of a wavelet [8]. A higher value of the Q-factor indicates a higher level of oscillation. Four wavelets and their frequency spectra are shown in Figure 1. The Q-factors of the waveforms are also given. It can be seen that waveform 1 and waveform 2 have different oscillatory behaviors, however, their frequency spectra share the same center frequency. The same can be observed for waveform 3 and waveform 4. Under such circumstances, frequency-based band-pass filters would not be able to separate waveforms 1 and 2, nor waveforms 3 and 4. However, they can be separated according to their Q-factors. It is calculated that waveforms 1 and 3 have a Q-factor of 1 since they exhibit low oscillatory behavior, and waveforms 2 and 4 have a Q-factor of 5 since they have relatively high oscillatory behavior. Additionally, this demonstrates that waveforms that have the same oscillatory behavior have the same the Q-factor, even if the center frequencies are different. This makes the OBSD effective for capturing the true features that are useful for bearing fault signature extraction under time-varying speed conditions.

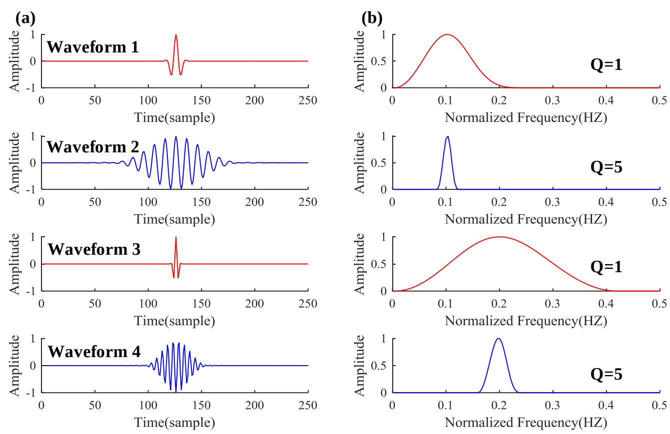

Figure 1 Wavelets and their frequency spectra

The OBSD method employs the Tunable Q-factor Wavelet Transform (TQWT) and Morphological Component Analysis (MCA) to realize the signal decomposition [6]. The TQWT is used to generate a set of wavelets that have the same Q-factor, i.e. the same oscillatory behavior. The wavelets can be obtained with the selection of three parameters, Q (Q-factor), r and P, where Q is related to the oscillatory behavior, r is related to the redundancy of the frequency responses, and P is the number of wavelets. By setting up two sets of wavelets, one with low oscillatory behavior with parameters Q_l, r_l, and P_l, and the other set with high oscillatory behavior with parameters Q_h, r_h, and P_h, then the signal decomposition can be completed by MCA. The wavelet coefficients are obtained via optimization [6] as

$$\begin{bmatrix} \mathbf{w}_h^{opt} \\ \mathbf{w}_h^{opt} \end{bmatrix} = \underset{\mathbf{w}_l, \mathbf{w}_h}{arg\,\min} \left\| \mathbf{y} - \mathbf{S}_l \mathbf{w}_l - \mathbf{S}_h \mathbf{w}_h \right\|_2^2 + \lambda_l \left\| \mathbf{w}_l \right\|_1 + \lambda_h \left\| \mathbf{w}_h \right\|_1 \quad (1)$$

where $\mathbf{w}_l$ refers to wavelet coefficients for the low oscillatory component, $\mathbf{w}_h$ stands for the wavelet coefficients for the high oscillatory component, $\mathbf{w}_l^{opt}$ and $\mathbf{w}_h^{opt}$ are results after optimization, $\mathbf{y}$ is the signal to be decomposed, $\mathbf{S}_l$ refers to wavelets obtained via the TWQT for the low oscillatory component, $\mathbf{S}_h$ represents wavelets for the high oscillatory component, λ_l is the regularization parameter for the low oscillatory component, λ_h is the regularization parameter for the high oscillatory component, and $\| \ \|_1$ and $\| \ \|_2$ are the norm-1 operation and the norm-2 operation, respectively. This optimization problem can be solved using an iterative algorithm called the Split Augmented Lagrangian Shrinkage Algorithm (SALSA), obtained as [6]

$$\mathbf{w}_i^k = f\left(\mathbf{w}_i^{k-1}, \mu\right),\ i = l, h,\ k = 1, 2, ..., K \qquad (2)$$

where μ is the penalty parameter and K is the maximum number of iterations. Details of the solution can be found in the appendix in [7]. By selecting the maximum number of iterations, the optimal wavelet coefficients are obtained as

$$\mathbf{w}_i^{opt} = \mathbf{w}_i^K,\ i = l, h \qquad (3)$$

With the calculated wavelet coefficients, the decomposed low oscillatory and high oscillatory components can then be obtained by inverse TQWT with the optimized wavelet coefficients.

III. IMPLEMENTATION OF OBSD ON BEARING FAULT FEATURE EXTRACTION UNDER TIME-VARYING SPEED CONDITIONS

According to the characteristics of the bearing fault-induced signal and the interference signal, the bearing fault-induced signal is more impulsive. which can be considered as low oscillatory behavior, and the interference is smoother which can be considered as high oscillatory behavior [9]. Therefore, the decomposed low oscillatory component and the high oscillatory component via the OBSD are taken to be the bearing fault signature and interference, respectively.

The bearing fault-induced signal can be simulated as impulse responses which occur at the FCF along the time span [10]. For a bearing operating under time-varying speed conditions, the equation is given as [11]

$$x(t) = \sum_{m=1}^{M} L_m e^{-\beta(t-t_m)} \sin\left[\omega_r\left(t - t_m\right) + \phi_m\right] u\left(t - t_m\right) \qquad (4)$$

where M is the number of impulse responses which is determined by the signal length T and Instantaneous Fault Characteristic Frequency (IFCF), L_m is the amplitude of the mth impulse response, β is the coefficient related to damping, ω_r is the excited resonance frequency or damped frequency of the vibration system, ϕ_m is the phase of the mth impulse response, and $u(t)$ is unit step function. In the previous equation, t_m is the occurrence time of the mth impulse response which is calculated as

$$\begin{cases} t_1 = \left(1 + \delta_1\right)\left[1/ f_c\left(t_0\right)\right] \\ t_m = \left(1 + \delta_m\right)\left[1/ f_c\left(0\right) + ... + 1/ f_c\left(t_{m-1}\right)\right] \ m = 2, 3, ..., M \end{cases} \qquad (5)$$

where t_0=0, δ_m is the random slippage ratio with the average varying between 0.01 and 0.02, $f_c(t)$ denotes the IFCF, and the time interval between the (m-1)th impulse response and the mth impulse response is (1+δ)/ $f_c(t_{m-1})$.

The interference signal can be simulated as the sum of sinusoidal functions of the frequency of the interference and its harmonics, given as [11]

$$h(t)=\sum_{n=1}^{N} B_n \sin(2\pi n f_h t) \tag{6}$$

where N is the number of sinusoidal functions, B_n is the amplitude, and f_h is the time-varying frequency of the interference, called Instantaneous Interference Frequency (IIF) in this paper.

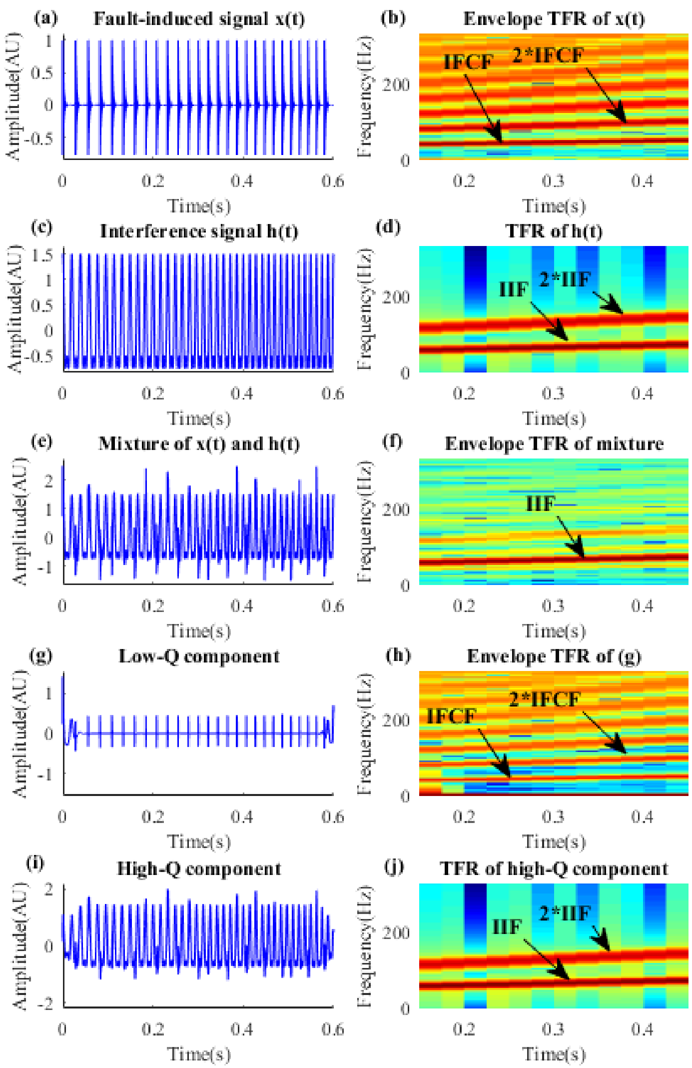

Figure 2 Implementation of the OBSD on bearing fault signature extraction under time-varying speed conditions

An example of the implementation of the OBSD on bearing fault signature extraction is illustrated in Figure 2. The original signal, shown in Figure 2(e), is a mixture of bearing fault impulses (Figure 2(a)) and interference (Figure 2(c)). The bearing fault signal is modeled by equation (4) with IFCF $f_c(t)$=35t+35 Hz, L_m=1, β=500, ω_r=4000*2π rad/s, ϕ_m=0, δ_m=0.01 and signal length T=0.6s. In addition, the interference is modeled by equation (6) with f_h=50t+50 Hz, N=2 and B_n= [1, 0.5]. Under constant speed, the bearing fault is generally detected by the envelope spectrum which is the spectrum of the envelope preceded by the computation of a Hilbert transform [2]. Under time-varying speed, since the IFCF and its harmonics are time-varying, they can be observed in the Time-Frequency Representation (TFR) obtained via Short-Time Fourier Transform (STFT) [12]. As shown in Figure 2(b), the envelope TFR of the bearing fault-induced signal is composed of time-frequency curves at IFCF and its multiples, which can be used to detect the presence of a bearing fault. Similarly, the frequency of interference IIF and its 2nd harmonic show curves in the TFR of the interference signal, shown in Figure 2(d). However, it can be seen from Figure 2(f) that the envelope TFR of the original signal is dominated by the IIF, which implies that the bearing fault cannot be detected without additional signal treatment. By applying the OBSD to the contaminated original signal with OBSD parameters Q_l=1, r_l=6, P_l=40, Q_h=6, r_h=6, P_h=124, λ_l=λ_h=0.3, μ=2 and K=150, the signal is decomposed into a low oscillatory component (shown in Figure 2(g)) and a high oscillatory component (shown in Figure 2(i)). The bearing fault-induced impulses, which is the fault signature, are clearly seen in the low oscillatory component (Figure 2(g)). Furthermore, the envelope TFR of the low oscillatory component, shown in Figure 2(h), is dominated by the IFCF and its harmonics which is the same case as in Figure 2(b). The bearing fault can thus be easily detected. Additionally, the TFR of the high oscillatory component shown in Figure 2(j) is dominated by the IIF and its 2nd harmonic, which is the same case as in Figure 2(d). It can be seen from this implementation that the OBSD can be effectively used to separate the bearing fault signature from a signal contaminated by interference under time-varying speed conditions.

IV. EXPERIMENTAL EVALUATION

To test the performance of the OBSD method for bearing fault signature extraction under time-varying speed conditions, it is applied to signals collected from an experiment. The experiment is conducted on a SpectraQuest machinery fault simulator (MFS-PK5MT) to collect the bearing vibration signal which is contaminated by interference transmitted from a gearbox and noise.

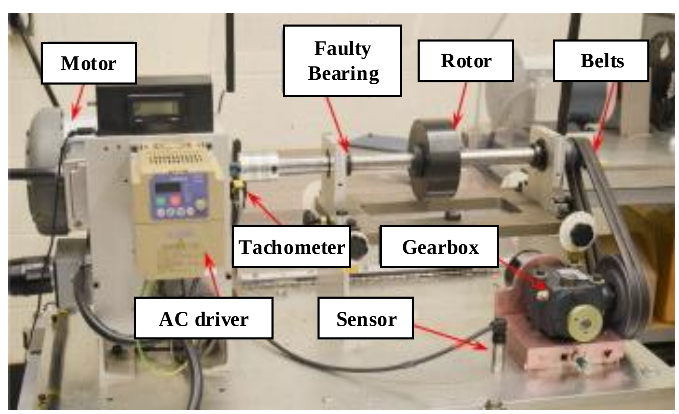

Figure 3 Experimental set-up

The set-up of this experiment is shown in Figure 3. The shaft is supported by two bearings and one of them is a faulty bearing with an outer race fault. The shaft is driven by a motor and the motor is controlled by an AC drive. A gearbox is connected to the shaft by a belt. Dimensions of bearings and gears used in this experiment are given in Table I. The IFCF is 3.57 times the shaft rotational frequency and the gear meshing frequency is (18/2.6)=6.92 times the shaft rotational frequency. A sensor (accelerometer) is mounted on the base of the test rig to collect the vibration signal. Therefore, the collected signal contains not only the bearing vibration signal but also the gear meshing signal. The signal is sampled by Labview with sampling frequency 20kHz and the duration of the signal is 4.46s. Additionally, to verify the results obtained by the proposed method, a tachometer is used to measure the time-varying shaft rotational speed.

Table I Dimensions of bearings and gears

Bearing type	**Pitch diameter**	**Ball diameter**	**Number of balls**	**BPFO**
ER16K	38.52mm	7.94mm	9	$3.57f_r$
Diameter ratio of sheaves		**Number of teeth**	**Gear meshing frequency**	
1:2.6		18	$6.92f_r$	

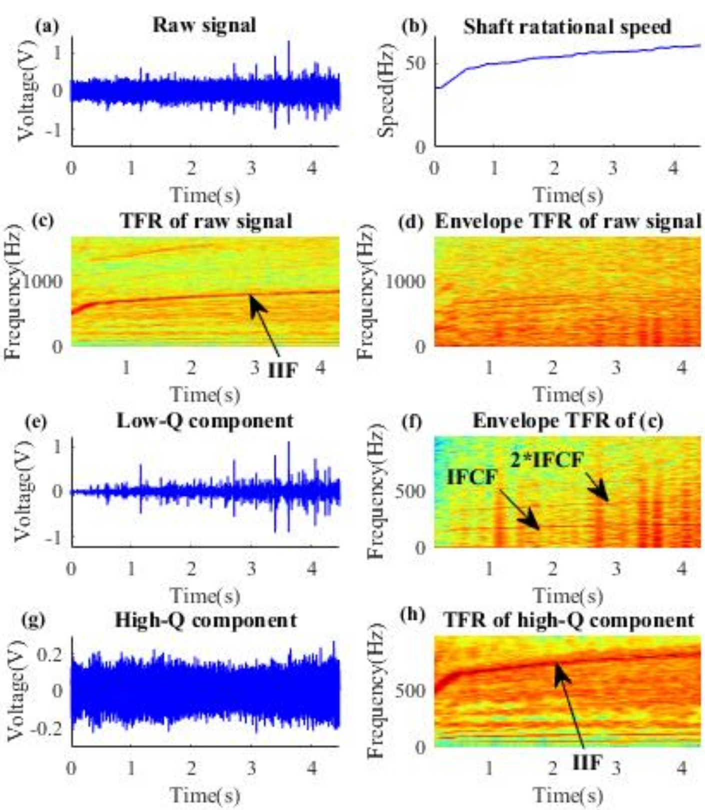

Figure 4 Results of the experiment

The collected raw signal is shown in Figure 4(a) and the measured ISRF is shown in Figure 4(b) which increases from 30.25Hz to 60.5Hz. The TFR of the raw signal is obtained via the STFT, as shown in Figure 4(c). It can be seen that the TFR of the raw signal is dominated by the instantaneous gear meshing frequency, i.e. the IIF. The IFCF and its harmonics cannot be observed. Moreover, in the envelope TFR of the raw signal, shown in Figure 4(d), no clear T-F curves can be observed. Obviously, the bearing fault cannot be detected and diagnosed with the raw signal directly.

The OBSD is then applied to the raw signal with parameters Q_l=1, r_l=6, P_l=51, Q_h=8, r_h=6, P_h=210, λ_l=λ_h=0.1, μ=1 and K=250. The decomposed low oscillatory component is shown in Figure 4(e) and the high oscillatory component is shown in Figure 4(g), respectively. The envelope TFR of the low oscillatory component is obtained via the Hilbert transform and STFT, shown in Figure 4(f). The IFCF and its harmonics can be observed in Figure 4(f) without the presence of the IIF and its harmonics. The TFR of the high oscillatory component is also obtained (Figure 4(h)) in which the IIF can be observed without the IFCF and its harmonics. The results in Figure 4(f) and Figure 4(h) demonstrate that the OBSD has effectively separated the bearing fault signature and the interference. Therefore, the OBSD can be effective for bearing fault signature extraction under time-varying speed conditions.

V. CONCLUSIONS

In this paper, the performance of the OBSD for bearing fault signature extraction under time-varying speed conditions was examined via experimental data. The results show that the OBSD can be effectively used to extract the bearing fault signature with the presence of an interference signal.

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