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Intelligent bearing fault detection by enhanced energy operator

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ABSTRACT

In this paper, we propose an intelligent bearing fault detection method based on a calculus enhanced energy operator (CEEO). The main purpose is to extract the bearing fault signatures in the presence of strong noise and multiple vibration interferences without prior information of the resonance excited by the bearing fault. This new energy operator exploits both the interference handling capability of a differentiation step and the noise suppression nature of the integration process. It also shares the simplicity, computational efficiency, and the ability to reveal signal impulsiveness of the energy operator. All these elements, i.e., differentiation, integration and energy operator, are implemented by a simple formula in a single step. Another advantage of the CEEO method is that, unlike the popular high frequency resonance methods, it does not require a bandpass filtering step and hence eliminates the burden to acquire the resonance information. As such, it is suited to on-line bearing fault detection in a noisy environment with multiple vibration interferences. Our simulation studies have shown that the CEEO method outperforms the conventional energy operator and the enveloping methods in handling both noise and interferences. Its performance has also been examined using our experimental data and the data from the literature.

1. Introduction

Bearings are widely used in mechanical systems and yet are among the most failure-prone components. An effective bearing condition monitoring method can prevent catastrophic failure of the equipment, and reduce cost of repair and down time. Many signal processing methods have been explored for bearing fault detection. However, weak fault signatures can be masked by noise from different external sources and internal mechanical components which makes bearing fault detection a very challenging task.

Vibration signals are commonly used for bearing condition monitoring because they are information-rich and the sensors are inexpensive and easy to implement. The vibration analysis methods for bearing fault detection can be classified into time-domain, frequency-domain, and time–frequency approaches. Statistical indicators such as root mean square, crest factor, and kurtosis are often adopted in the time-domain analysis (Kiral & Karagülle, 2003; Tao et al., 2007; Wang & Golnaraghi, 2010). Comparing such statistical values with the historical data of the same indicator can be helpful for fault recognition in the system (Decker, 2002; Samuel & Pines, 2005; Samuel & Pines, 2009). Therefore, time-domain methods sometimes rely on prior knowledge of the healthy-state information of mechanical components.

In order to extract certain fault signatures, a signal in time domain can be transformed into frequency domain representation. The most applicable methods of the frequency-domain approach in industry are high-frequency resonance (HFR) techniques. When faults come in contact with the mating surface during bearing operations, they generate impulses and excite the resonance frequency (McFadden & Smith, 1984; Sheen, 2004; Sheen, 2007). The HFR techniques extract the bearing fault signature, i.e., the fault characteristic frequency based on the excitation resonance information. The faulty features in the acquired signal manifest the impulsive vibration generated due to fatigue cracks or spalls on the surface of the bearing, namely inner race, outer race and rollers. The HFR technique involves bandpass filtering the raw vibration signal around high-frequency resonance band and amplitude demodulation (AD) prior to spectral analysis of the signal (McFadden, 1986; Tandon & Choudhury, 1999; Wang, 2001). Its performance heavily relies on designing appropriate bandpass filter which is ideally defined by an optimum band width, and centre frequency according to the resonance frequency characteristics. Many studies have been carried out to estimate bandpass filter parameters. For example, Antoni and Randall introduced a spectral kurtosis approach for this purpose (Antoni & Randall, 2006; Barszcz & Randall, 2009).

Vibration signal can also be examined by the joint time–frequency analysis. Commonly used time–frequency methods include short-time Fourier transform (STFT), Wigner–Ville

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distribution (WVD), and Choi–William distribution (CWD) (Wang & McFadden, 1993a; Wang & McFadden, 1993b; Dong & Chen, 2012; Williams & Zalubas, 2000; Baydar & Ball, 2001). Investigation of non-stationary signals is the main purpose of the time–frequency analysis. However, the time–frequency methods have some problems, e.g., the STFT method suffers from the resolution problem, the WVD has the cross-term problem, and the CWD is slow and hence may not be suited to on-line applications.

Another popular time–frequency analysis approach to machine fault diagnosis is wavelet transform (Nikolaou & Antoniadis, 2002; Peng & Chu, 2004; Staszewski & Tomlinson, 1994). The effectiveness of a certain wavelet transform methods is often dependent on the proper selection of the wavelet parameters (Bozchalooi & Liang, 2007). Therefore, similar to the high-frequency resonance technique, a problem arises with parameter selection and re-calibration.

In real applications, it is desirable to develop online bearing monitoring methods that are independent of prior knowledge, nonparametric, non-filtering, easy to implement, and computationally efficient. As such, a nonparametric method was suggested by Bozchalooi and Liang (2009). This parameter-free fault detection algorithm employs the differentiation of a signal with maximum likelihood estimation as its basis. Furthermore, Liang and Bozchalooi presented another parameter-free method based on the energy operator approach for bearing fault detection (Liang & Bozchalooi, 2010). They have demonstrated that the nonparametric methods such as the differentiation of signals and the energy operator have a great potential to replace the HFR techniques. Several other researchers have also contributed to the literature on the use of energy operators to bearing fault detection, e.g., the studies reported by Henríquez Rodríguez, Alonso, Ferrer, and Travieso (2013) and Li and Zheng (2008).

In this paper, an intelligent nonparametric method with better noise handling capability will be developed to complement the energy operator method. It can automatically extract the fault information without the need of prior resonance information. This method is based on the following observations (the details will be illustrated in later sections):

1. The differentiation of a signal can boost signal-to-interference ratio (SIR) and hence enhance the detectability of the impulsive fault signal, but in the meantime also amplify the high frequency noise.
2. The integration of a signal can suppress the high frequency noise but may jeopardize the detection of the impulsive fault signal due to its "smoothing" effect.
3. The energy operator can quickly reveal impulsive signal component without filtering if the noise level is relatively low.

These observations motivate us to develop a new method consisting of three main steps: (a) differentiate the signal to boost the SIR especially in the presence of multiple strong interferences, (b) integrate the result of step (a) to improve the signal-to-noise ratio (SNR) particularly for noisy signals, and (c) apply the energy operator to the result of step (b) to detect the fault. To facilitate applications, the three steps will be incorporated into a single calculus enhanced energy operator (CEEO).

The paper hereafter is organized as follows: Section 2 illustrates that the signal differentiation can increase SIR and hence the detectability of the fault from a faulty bearing signal with vibration interferences. Section 3 examines the effect of signal integration on high frequency noise suppression. Section 4 presents a layer operator consisting of sequential operations of signal differentiation and integration. In Section 5, the calculus enhanced energy operator (CEEO) is introduced based on the energy operator and the layer operator concepts. It is shown that the CEEO method can enhance signal in the presence of noise in comparison with the energy operator and envelope method. In Sections 6 and 7, the proposed method is evaluated using simulated signals and experimental data respectively. Finally, the conclusions are given in Section 8.

2. The effect of signal differentiation

This section starts with an illustrative example to explain that the low frequency signal components can be suppressed and the high frequency ones can be enhanced by differentiation. Then we quantify the level of signal enhancement by deriving the SIR. Next the effects of signal differentiation on interferences and noise are illustrated using simulation data.

For discrete signal, the differentiation becomes difference as follows (step $\Delta t = 1$). At time n, the discrete backward difference is written as

$$\mathrm{D}(x(n)) = x(n) - x(n-1) \tag{1}$$

Now we consider a signal with a low frequency component (0.1 Hz) and a high frequency component (10 Hz) of the same amplitude (Fig. 1(a)). The difference of the signal is shown in Fig. 1(b) which demonstrates that the low frequency component has been suppressed whereas the strength of high frequency one has been enhanced relative to that of the low frequency component. This effect is useful to suppress low frequency interferences and noise.

2.1. Evaluation of the signal differentiation on the enhancement of SIR

To evaluate the effect of signal differentiation on SIR when the fault bearing signal contains multiple interferences, we use a simple bearing model as shown (Bozchalooi & Liang, 2009; Ho & Randall, 2000; Liang & Bozchalooi, 2010):

$$r(t) = x(t) + \upsilon(t) = Ae^{-\beta t}\cos(\omega_r t + \varphi) + \sum_{k=1}^{K} L_k \cos \omega_{Ik} t \tag{2}$$

where A is the amplitude of the fault signal, β is the structural damping characteristic, ω_r is the frequency of the excited resonance, ω_{Ik} represents the frequency of kth interference component, L_k denotes the amplitude of the kth interference component, $x(t)$ is the vibration signal containing fault generated impulse, $\upsilon(t)$ contains multiple vibration interferences. Due to practical reason we assume that the excited resonance frequency is much higher than interference signal frequency ω_{Ik} for all k's. The derivative of the signal shown in Eq. (2) in continuous form is

$$\mathrm{D}(r(t)) = -A\omega_r e^{-\beta t}\sin(\omega_r t + \varphi) - A\beta e^{-\beta t}\cos(\omega_r t + \varphi) - \sum_{k=1}^{K}\omega_{Ik} L_k \sin \omega_{Ik} t \tag{3}$$

Eq. (3) can be written as

$$\mathrm{D}(r(t)) = -\lambda e^{-\beta t}\cos(\omega_r t + \varphi_\varsigma) - \sum_{k=1}^{K}\omega_{Ik} L_k \sin \omega_{Ik} t \tag{4}$$

where

$$\lambda = A\sqrt{\omega_r^2 + \beta^2}, \quad \sin\varsigma = \frac{A\omega_r}{\lambda}, \quad \cos\varsigma = \frac{A\beta}{\lambda}, \quad \varphi_\varsigma = \varphi - \varsigma$$

The signal-to-interference ratio of a fault bearing signal with multiple interferences can be defined as (Liang & Bozchalooi, 2010)

$$\mathrm{SIR}\,(r) = \frac{(1/T)\int_0^T x^2(t)\mathrm{d}t}{(1/T)\int_0^T \sum_{k=1}^{K} \upsilon_k^2(t)\mathrm{d}t} = \frac{P_x}{P_\upsilon} \tag{5}$$