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Research Article

A hybrid fault diagnosis method based on second generation wavelet de-noising and local mean decomposition for rotating machinery

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ABSTRACT

In order to extract fault features of large-scale power equipment from strong background noise, a hybrid fault diagnosis method based on the second generation wavelet de-noising (SGWD) and the local mean decomposition (LMD) is proposed in this paper. In this method, a de-noising algorithm of second generation wavelet transform (SGWT) using neighboring coefficients was employed as the pretreatment to remove noise in rotating machinery vibration signals by virtue of its good effect in enhancing the signal–noise ratio (SNR). Then, the LMD method is used to decompose the de-noised signals into several product functions (PFs). The PF corresponding to the faulty feature signal is selected according to the correlation coefficients criterion. Finally, the frequency spectrum is analyzed by applying the FFT to the selected PF. The proposed method is applied to analyze the vibration signals collected from an experimental gearbox and a real locomotive rolling bearing. The results demonstrate that the proposed method has better performances such as high SNR and fast convergence speed than the normal LMD method.

1. Introduction

Rotating machines are often caught in the malfunctions or faults during the operating process because of the damages of some key components. These faults may cause abnormal operation and, if not detected early, can cause emergency shutdown and even equipment breakdown or casualties. Therefore, the efficient and accurate fault diagnosis technique is very important for guaranteeing reliability and performance of a mechanical system, production efficiency and plant safety [1,2]. Due to the sensitivity of vibration signals, vibration based time–frequency analysis to the mechanical vibration signals has become a most successful and effective technique in recent years [3,4]. Some improved methods are designed for fault detection, such as wavelet packet transform (WPT) [5,6], empirical mode decomposition (EMD) [7,8], and so on. However, WPT requires choosing wavelet basis and decomposing layers, which makes it a non-adaptive signal processing method in nature [9]. EMD method can self-adaptively decompose a complex signal into a set of intrinsic mode functions (IMFs) and a residual. But, it still has some shortcomings, such as end effects [9], and modes mixing [10,11] that are still underway.

Local mean decomposition (LMD), a novel self-adaptive time–frequency analysis method, was proposed by Smith [12]. It is suitable to be applied to adaptively decompose the nonlinear and non-stationary vibration signals into a series of product functions (PFs), each of which is the product of an envelope signal and a purely frequency modulated signal from which instantaneous frequencies with physical significance can be obtained. Compared with EMD, one very useful property of the LMD method is that it directly gives access to the calculations of the instantaneous amplitude (IA) and instantaneous frequency (IF) without further applying Hilbert transform (HT) [13]. In addition, the LMD iteration process uses smoothed local means and local magnitudes so that envelope errors caused by the cubic spline approach used in the EMD can be avoided, and then the precision of the instantaneous frequencies and amplitudes will not be influenced [12,14]. Till now, the LMD method has been widely used in many fields, especially in the field of condition monitoring and fault diagnosis of various rotating machinery [14–16]. However, in actual fault diagnosis of mechanical equipment, the collected vibration signals which working in bad environment, not only contain useful features but also have much noise. The LMD method is greatly influenced by noise, mostly to increase a lot of extra and useless frequency component, to the practical application of LMD difficult [17]. Therefore, a critical step before extracting useful information from vibration signals.

With the continually development of wavelet theory, the wavelets de-noising technique has obtained a good signal–noise ratio (SNR) in signal de-noising, for example, Donoho [18] and Donoho and Johnstone [19] used scalar wavelet thresholding to de-noising and proved its validity. However, these methods only

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concerned one point and thresholded the signal term-by-term, which neglect the correlation between wavelet coefficients and fault features and cannot accurately extract weak fault features. Thus, Cai and Silverman [20] proposed a thresholding scheme by taking neighbor coefficients into account, and experimental results showed that neighboring coefficients thresholding has better performance on noise reduction than the traditional term-by-term wavelet de-noising.

Considering that the choice of the wavelet basis function influences the performance of fault feature extraction, the second-generation wavelet transform (SGWT) developed by Sweldens [21,22] is used here. It is a new wavelet construction method using lifting scheme in the time domain. Compared with the wavelets, the SGWT provides a great deal of flexibility and freedom for the construction of biorthogonal wavelets in the spatial domain, and can be used to construct customized wavelets by the design of prediction operator and update operator [23,24]. Under the same

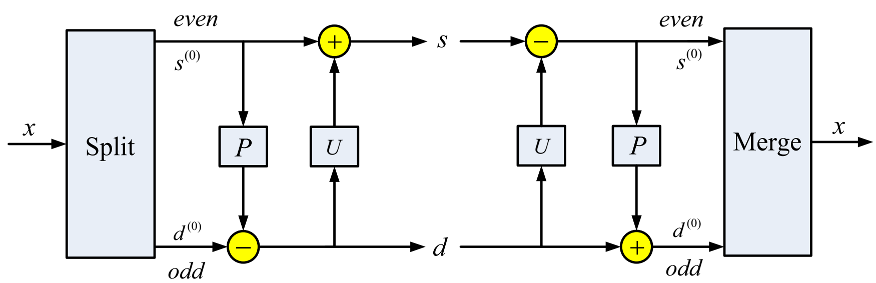

Fig. 1. The forward and inverse transform of SGWT lifting scheme.

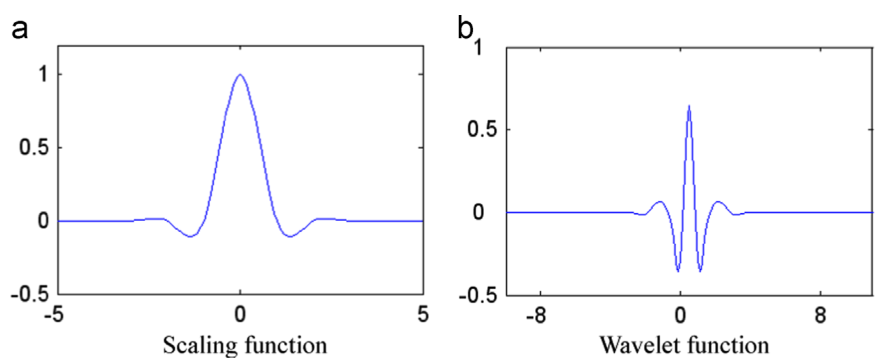

Fig. 2. The lifting scheme scaling function and wavelet function with $N=6$ and $\tilde{N}=6$.

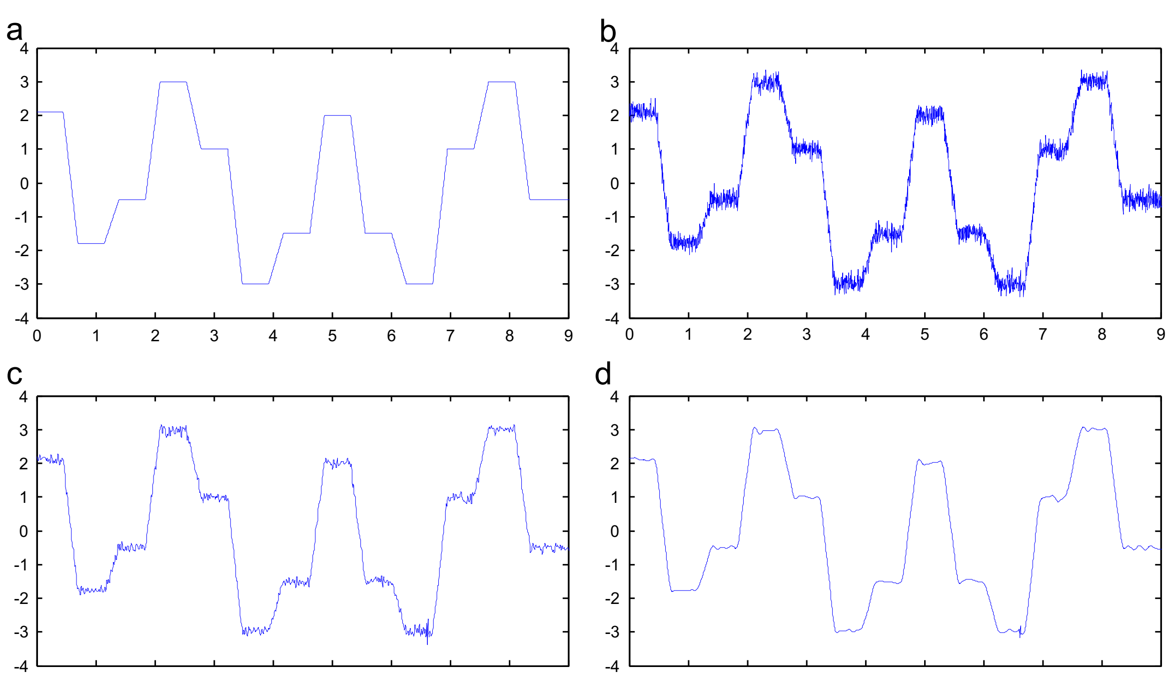

Fig. 3. Simulated signal: (a) Signal without noise; (b) Signal with noise; (c) the purified signal using Daubechies 5 wavelet with neighbor coefficients; (d) the purified signal using SGWD with neighbor coefficients.