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Time–frequency analysis based on ensemble local mean decomposition and fast kurtogram for rotating machinery fault diagnosis

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ABSTRACT

A time–frequency analysis method based on ensemble local mean decomposition (ELMD) and fast kurtogram (FK) is proposed for rotating machinery fault diagnosis. Local mean decomposition (LMD), as an adaptive non-stationary and nonlinear signal processing method, provides the capability to decompose multicomponent modulation signal into a series of demodulated mono-components. However, the occurring mode mixing is a serious drawback. To alleviate this, ELMD based on noise-assisted method was developed. Still, the existing environmental noise in the raw signal remains in corresponding PF with the component of interest. FK has good performance in impulse detection while strong environmental noise exists. But it is susceptible to non-Gaussian noise. The proposed method combines the merits of ELMD and FK to detect the fault for rotating machinery. Primarily, by applying ELMD the raw signal is decomposed into a set of product functions (PFs). Then, the PF which mostly characterizes fault information is selected according to kurtosis index. Finally, the selected PF signal is further filtered by an optimal band-pass filter based on FK to extract impulse signal. Fault identification can be deduced by the appearance of fault characteristic frequencies in the squared envelope spectrum of the filtered signal. The advantages of ELMD over LMD and EEMD are illustrated in the simulation analyses. Furthermore, the efficiency of the proposed method in fault diagnosis for rotating machinery is demonstrated on gearbox case and rolling bearing case analyses.

1. Introduction

Rotating machinery is a significant part of major equipment. The malfunction of rotating machinery usually causes a decrease in performance. In the worst case, it results in break-down of whole system, or even catastrophic failure with enormous economic losses and safety problems. To avoid occurrence of unexpected shutdown, fault diagnosis methods are widely adopted in industrial applications [1,2]. Vibration-based fault diagnosis techniques are known as effective methods in structural damage detection [3] and rotating machinery fault diagnosis [4]. These techniques can basically category into: time-domain analysis, frequency-domain analysis and time–frequency analysis methods. Because of losing information in one domain, time-domain analysis and frequency-domain analysis methods seem to be insufficient in the case of non-stationary signals [5]. Accordingly, a number of time–frequency analysis methods such as Wigner–Ville distribution

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(WVD), wavelet transform (WT), sparse decomposition and empirical mode decomposition (EMD) were developed in the field of fault diagnosis. However, these methods have inherent limitations. For instance, WVD is restricted by the cross-interference items [6]. Wavelet basis function and decomposition level need to be empirically chosen during analyzing practical signal, which makes WT non-adaptive [7,8]. The sparse decomposition heavily depends on the design of the redundant atom library and decomposition algorithm [9,10]. In fact, practical vibration signals contain complex, non-stationary, noisy, and nonlinear components, and non-adaptive signal processing approaches are not efficient for practical signal processing and analysis [11]. EMD adaptively decomposes any signal into a set of intrinsic mode functions (IMFs) which can be regarded as the basis functions derived from the nature of signals [12]. However, the efficiency of the EMD method is confined by the problems of end effects and mode mixing. There has been a great deal of literatures on these two aspects [13–16].

Local mean decomposition (LMD) which has the similar principles as EMD was originally developed by Smith [17] to process the electroencephalogram signal in 2005. Adequate ability in demodulation analysis makes the LMD qualified for decomposing complicated signals into relatively simple signals. Subsequently, it was introduced and has been given great attention in the field of fault diagnosis for rotating machinery [18–22]. Compared with EMD, LMD seems to be more suitable and has a better performance in fault detection [18–21]. First, LMD directly derives instantaneous amplitude (IA) and instantaneous frequency (IF) without Hilbert transform (HT) and yields more accurate results accordingly. Second, EMD uses cubic spline to fit lower and upper envelope, which may be affected by overshoot and undershoot and result in false components. Third, LMD decomposes signals into fewer levels than EMD which means that the useful information is more concentrated. However, like EMD, LMD still faces the problems of end effects and mode mixing. By extending the waveform based on spectral coherence it is possible to alleviate the end effects [22] since thus, it can maintain the continuity of the signal in time domain and frequency domain at end points. Mode mixing which results from intermittent signal may severely distort the decomposition results of LMD and make them uninterpretable. To reduce the mode mixing, ensemble local mean decomposition (ELMD) based on noise-assisted analysis was proposed by Yang et al. [23] and presented better performance than ensemble empirical mode decomposition (EEMD) in fault diagnosis. In the ELMD, first of all, independent white noises with finite amplitude are added into the raw signal. Then, LMD is applied to separately decompose the noise-added signals into a set of product functions (PFs). Finally, the final PFs are obtained by taking the ensemble means of respective PFs in each trial. The third step is used to eliminate the added noise in each PF. Sun et al. [24] combined ELMD and high-order ambiguity function to locate the natural gas leakage. Furthermore, aiming at enhancing the performance of ELMD, Zhang et al. [25] developed an optimized ELMD and adopted it to detect fault for mechanical components. However, after the signal is decomposed by ELMD, the existing noise in the raw signal remains in corresponding PF with the component of interest according to the filter bank structure of LMD. Thus further procedure is required to detect the fault characteristic information in a precise way.

Spectra kurtosis (SK) method was originally proposed by Dwyer [26] to characterize transient signals in data. The basic idea of SK is to calculate the kurtosis index, which is sensitive at the presence of transient signals, so as to reflect how many non-stationary components are contained at each frequency line. Antoni [27,28] conducted intensive research relevant to SK and proposed a time–frequency analysis method named "kurtogram" which can be described as a cascade of SK calculated by short time Fourier transform (STFT) with different time window lengths. To make on-line industrial applications accessible, fast kurtogram (FK) was developed, which presented adequate efficiency in transient fault detection [29]. The impulses are extracted and highlighted after the raw signal is processed by the band-filter of which the center frequency and bandwidth are optimized by FK. Barszcz and Randall [30] adopted FK to detect the tooth crack in the planetary gear of a wind turbine and yielded good results. Zhang and Randall [31] combined genetic algorithms and FK to optimize the parameters of the band-filter in fault diagnosis for rolling bearing. Wang et al. [32] combined the minimum entropy de-convolution and FK for rolling bearing early stage fault feature extraction. Despite of the efficiency, FK reveals its weakness when there are strong non-stationary interference vibration contents in the raw signal [33]. In addition, when the decomposition level is confirmed, the center frequency and the frequency resolution taken into consideration are limited. Namely, the optimal filter is nominal.

Considering the above all, a time–frequency analysis method which combines ELMD and FK for rotating machinery fault detection is proposed. Firstly, the original signal collected from rotating machinery is decomposed into a set of mono-components by using ELMD. Based on noise-assisted approach, ELMD resolves the mode mixing problem of LMD. Then, the PF with highest kurtosis value is selected for further analysis. Finally, the selected PF signal is filtered by an optimal band-pass filter based on FK to extract impulse signal. The diagnosis result can be deduced according to the appearance of fault characteristic frequencies in squared envelope spectrum.

The remainder of this paper is organized as follows. The ELMD and FK are briefly introduced and the comparisons of LMD, EEMD and ELMD in simulation analyses are illustrated in Section 2. In Section 3, a time–frequency analysis method based on ELMD and FK is detailed. Section 4 presents the applications of the proposed technique in fault diagnosis for rotating machinery and the comparison analyses of individual ELMD method, FK method and proposed method. Some concluding remarks are summarized in Section 5.