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Improved Hilbert–Huang transform based weak signal detection methodology and its application on incipient fault diagnosis and ECG signal analysis

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ABSTRACT

In the present study, a weak signal detection methodology based on the improved Hilbert–Huang transform (HHT) was proposed. Aiming to restrain the end effects of empirical mode decomposition (EMD), wavelet analysis was embedded in iteration procedures of HHT to remove iterative errors as well as noise signal in the sifting process. Meanwhile, a new stopping criterion based on correlation analysis was proposed to remove undesirable intrinsic mode functions (IMFs). Results of analyzing synthetic signal, incipient rotor imbalance fault of Bently test-rig and weak electrocardiogram (ECG) signal show that the improved HHT combined with wavelet analysis have excellent weak signal detecting performance whilst achieving robustness against low signal-to-noise ratio (SNR). Furthermore, comparative studies of the proposed method, the classical EMD method, and other four generally acknowledged improved EMD methods, as well as a widely used stopping criterion demonstrate that the proposed method significantly reduces end effects and removes undesirable IMFs.

1. Introduction

Signal detection technique has wide applications in the fields where noise and imperfect signals present challenges to the task of separating hits and correct rejections from misses and false alarms. Weak signal detection combined with artificial intelligent techniques and statistical approaches [1–3] will go a long way towards improving the correct evaluation on the present performance and providing lead time to make alternative prognostics. However, the detection of incipient failure is not straight forward due to weak signals with small amplitudes, strong background signals or noises, and also low signal-to-noise ratios (SNR).

With advances in digital signal processing methods, there has been an increasingly strong interest in the application of spectral analysis techniques in detecting weak signal. Owing to the advantage of direct association with rotating characteristics, Fourier transform (FT) based methods were the most used signal processing tool in rotating machinery signal analysis. The frequency domain decomposition (FDD) technique [4] was used to identify weak features of spindle-tool unit in high-speed machining. Weak traffic sign shape features detection and sign pattern recognition system were established on Fourier transform [5]. Fourier transform (FT) was adopted to investigate the vibration and current transients of a multistage gear box under transient loads [6]. However, incipient faults are always consisted in weak signals that have a greater number of transfer segments with small amplitude, and FFT based spectral analysis is ineffective under this condition because of the non-linear and non-stationary characteristics, as well as low signal-to-noise ratios [7].

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Many time-frequency analysis approaches have been introduced to overcome shortcomings of the conventional FFT in the past few years. Wavelet transform (WT) has multi-scale resolution in time-frequency analysis for characterizing the transitory features of non-stationary signals, and was widely applied on weak signal analysis. The application of wavelet packet decomposition (WPD) on detecting features from weak speech signal reveals that wavelet packet decomposition can lead to better representation of non-stationary parts of the weak speech signal and improve the noise robustness [8]. In a similar work by Akhtar et al. [9], wavelet analysis based signal denoising method was used to analysis biomedical signals with high level background noise and effectively detected artifacts produced in electroencephalographic (EEG) data by muscle activity, eye blinks and electrical noise. Also, wavelet analysis was employed to detect incipient fault features from three different failure types of a spur bevel gear box [10]. However, wavelet method uses a fixed decomposition scale for signal analysis and does not take signal's characteristics into consideration [11]. Besides, it is essentially a kind of Fourier transform with adjustable windows, and also suffers from leakage problem [12] that arises due to limited length of wavelet functions.

Pertinent literatures proposed other weak signal processing method. Neural-fuzzy networks were employed to model the dynamics of an electric power transmission system, and a statistical method was proposed for the early detection of cascading events in electric power systems [3]. Statistical methods were employed to detect early failures of cascading events in an electric power grid, and non-linear filters were used for the generation of residuals and to derive a fault threshold from the generalized likelihood ratio [13]. Signal-to-noise ratio of buried weak signals and standard-deviation of noisy spectral estimates are, respectively, enhanced and reduced by two denoising methods called, modified frequency extent denoising (MFED) and constant frequency extent denoising (CFED) [14,15]. A modified up-down counter detector was used to acquire weak GPS signals [16]. Mean shift based method was used to construct a self-adaptive model for ECG denoising, and achieved denoising performance for both normal and abnormal ECG signals with low SNR background noises [17]. However, drawbacks of mentioned weak signal processing methods are the low computational efficiency, and complexity of the numerical optimization procedures (see, for example [16]). Moreover, the obtained results were simulated by experimental random signals buried in white and colored noise (see, for example [17]), however, the real weak biomedical signal contains static electricity coupling interferences, body movement interferences, and electrode noises, which do not have the same characteristics with Gaussian noises. Meanwhile, when excited with sine bursts or colored noise, the oscillator remains most of the time on the lowest solution.

Recently, a new signal processing method called Hilbert–Huang transform (HHT) has been developed for non-linear and non-stationary signal analysis, and it was widely used in speech signal processing [18], biomedical engineering [19] and fault feature identification [20]. By employing empirical mode decomposition (EMD), the investigated signal was decomposed into a series of mono-component modes with local characteristic time scales, and then the instantaneous frequency of each IMF was represented through Hilbert transform. Nevertheless, the classical HHT suffers from end effects and redundant IMFs associated with EMD processes. Large swings occur in the interpolation fitting process, which eventually propagate inward and corrupt the whole data span, especially in the low-frequency components [21]. Many schemes have been proposed in literatures for the purpose of alleviating the end effects and removing redundant IMFs. Rilling et al. [22] used a data flipping (mirror) technique by adding two extreme points on each side of the signal to furnish a complete periodic cycle of the waveform to suppress the end effect. Xun and Yan [23] applied artificial neural networks (ANN) to extend each side of the signal and then perform EMD method. Cheng et al. [24] proposed an improved HHT method based on support vector regression machine (SVR). Roy and Doherty [25] introduced raised cosine interpolation to improve the classical EMD method. However, up-to-date improved EMD methods have following shortcomings. Firstly, these methods employ prediction approaches to improve the classical EMD method by extending each side of the signal, while signal extension methods such as support vector regression machine, artificial neural network, auto-regressive moving average and mirror extension methods cannot completely eliminate boundary distortion. Also prediction errors will propagate during the sifting process and corrupt all IMFs. Secondly, signals of mechanical failures in the initial state often have small amplitude and with low signal-to-noise ratio, while signal extension based EMD methods are verified through analyzing pure signal, and do not take weak signal with low signal-to-noise ratio into consideration. Thirdly, the extension part of each side of the signal is empirical and cannot reflect real features of the original weak signal. This paper dedicates to propose a weak signal detection scheme based on improved EMD method and wavelet analysis, which takes iterative errors of the sifting process and correlation relationship between each IMF and the original signal into consideration.

The remainder of this paper was organized as follows. In Section 2, the concept of empirical mode decomposition (EMD) was reviewed. In Section 3, the proposed solutions of restraining the end effects and removing redundant IMFs were discussed in detail. Comparative studies of the proposed method, the original EMD method, and other four generally acknowledged improved EMD methods, as well as a widely used stopping criterion were performed. In Section 4, the capabilities of proposed method on detecting weak signal was validated through analyzing the early stage of performance degradation process of Bently rotor testbed and the weak ECG signal. Finally, conclusions are drawn in Section 5.

2. The empirical mode decomposition

The EMD method introduced by Huang et al. [26] is relatively a new signal analysis tool. It develops from simple assumptions. (1) Any signal consists of different intrinsic modes of oscillations. (2) Every linear or non-linear mode has