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# Mono-component feature extraction for mechanical fault diagnosis using modified empirical wavelet transform via data-driven adaptive Fourier spectrum segment

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## ABSTRACT

Due to the multi-modulation feature in most of the vibration signals, the extraction of embedded fault information from condition monitoring data for mechanical fault diagnosis still is not a relaxed task. Despite the reported achievements, Wavelet transform follows the dyadic partition scheme and would not allow a data-driven frequency partition. And then Empirical Wavelet Transform (EWT) is used to extract inherent modulation information by decomposing signal into mono-components under an orthogonal basis and non-dyadic partition scheme. However, the pre-defined segment way of Fourier spectrum without dependence on analyzed signals may result in inaccurate mono-component identification. In this paper, the modified EWT (MEWT) method via data-driven adaptive Fourier spectrum segment is proposed for mechanical fault identification. First, inner product is calculated between the Fourier spectrum of analyzed signal and Gaussian function for scale representation. Then, adaptive spectrum segment is achieved by detecting local minima of the scale representation. Finally, empirical modes can be obtained by adaptively merging mono-components based on their envelope spectrum similarity. The adaptively extracted empirical modes are analyzed for mechanical fault identification. A simulation experiment and two application cases are used to verify the effectiveness of the proposed method and the results show its outstanding performance.

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## 1. Introduction

Mechanical fault diagnosis technology still is drawing lots of attentions for guaranteeing product quality and improving economic benefit. Due to heavy load and non-stationary conditions, bearings and some other important mechanical parts are inevitably damaged after long-term operation. As one of the most important and commonly damaged components, an unexpected mechanical fault may result in costly downtime and significant economic losses. Therefore, fault diagnosis, especially incipient faults, is of great importance to ensure the normal operation of the system. Among all mechanical condition monitoring and fault diagnosis techniques, vibration analysis has attracted sustained attention and has been studied widely because of its intrinsic advantage of revealing mechanical failure [1–3].

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When a local fault exists in a rolling element bearing, periodical impulses at the characteristic frequency will be produced, exciting resonance of bearings and decaying exponentially [4]. Hence, vibration signals of localized bearing defect reveal the feature of amplitude modulation. Because of that, demodulation analysis is often used to extract fault features and identify fault type for bearing fault diagnosis. Currently, the commonly used demodulation methods include Hilbert transform (HT) demodulation, energy operator demodulation and so on [5–7]. However, these mentioned methods are only effective when the signal is an AM-FM mono-component [8,9]. In fact, most machinery fault vibration signals are multi-component modulation signals. Thus, various methods are used to extract the fault-related mono-component or decompose a signal into a set of mono-components. Many advanced signal decomposition methods have been studied for fault feature extraction in the field of rotary machine diagnosis [10–13]. The typical multicomponent decomposition methods include wavelet transform (WT) and Hilbert–Huang transform (HHT) [14].

Wavelet transform (WT) is a powerful tool to analyze non-stationary signals [15]. A wavelet has good local time and frequency properties and WT provides time domain and frequency domain information by inner production between the analyzed signal and a predetermined wavelet basis [16]. Dyadic wavelet transform (DWT) are usually adopted for fault feature extraction. Its implementation is based on fast algorithms, saving a lot of computation time and DWT has gained fruitful applications in mechanical fault diagnosis [17,18]. Djebala used kurtosis to optimize DWT parameters for early bearing faults [19]. Kwak applied DWT-based soft thresholding denoising method to the cutting force signal in a turning process to monitor chatter vibration phenomenon [20]. However, DWT only decomposes the lowest frequency sub-band, which weakens its identification of fault features at high frequencies. Wavelet packet transform (WPT) is an extension of DWT and improves its frequency resolution through a parallel decomposition of both the high- and low-frequency bands [21]. Yen applied WPT to the neural network classification of vibration signals [22]. Fan combined WPT and Hilbert transform for early gearbox fault detection [23]. However, WPT follows the dyadic partition scheme and would not allow a data-driven frequency partition.

The Hilbert–Huang Transform (HHT), developed by Norden E. Huang, is an effective data-driven method for analyzing nonlinear and non-stationary signals [24]. The key part of this method is the Empirical Mode Decomposition (EMD) method. EMD decomposes the multi-modulated vibration signal into a few intrinsic mode functions (IMF). Each IMF is considered as a mono-component [25]. HHT has been widely used in rotary machine diagnosis because of its capability to separate a signal into IMFs with well-behaved Hilbert transform character [26]. Ricci introduced a merit index to automatically select the useful IMF for diagnosis of a spiral bevel gearbox [27]. Liu combined HHT, singular value decomposition and Elman neural network to classify bearing fault modes under different operating conditions [28]. However, weaknesses of EMD including sensitivity to noise, end effects, and mode mixing problem may cause IMFs to lose physical meanings [26]. It is also observed that EMD has shortcomings such as the first IMF covering too wide frequency range, and some signals with low-energy components being inseparable [29]. Moreover, Flandrin found that EMD acts essentially as a DWT-like filter bank for broadband stochastic processes [30], which motivates the researchers to consider wavelet transform as an alternative tool to decompose multicomponent signals [31].

Aiming at solving DWT's fixed dyadic frequency partition problem and achieving EMD-like adaptivity in WT, a novel wavelet transform, named empirical wavelet transform (EWT), is developed to extract meaningful modes from a signal [32]. EWT is a type of wavelet tight frame. The key hypothesis is that the signal is described as the sum of a few AM-FM mono-components which have compact support in Fourier spectrum. EWT constructs empirical wavelets adaptively by detecting Fourier spectrum segment of each mono-component and then decomposes the signal. Later, Gilles investigated a parameterless spectrum segment method for EWT based on scale space representation and K-Means clustering algorithm [33]. However, the work is motivated by academic interest and pays little attention to engineering demands. As a new signal processing method, how to extract empirical modes from a practical complicated mechanical signal with physical meanings is still a problem. When too fine frequency partition is set, many narrow band modes are extracted and there are two problems. First, several modes may show the same modulation information, resulting in unnecessary redundancy. Second, some important modulation information may be missed in a narrow band mode because Hilbert transform must satisfy Bedrosian theorem [34]. In the other hand, too coarse frequency partition will mix different mono-components and may introduce artifacts. To avoid this problem, a modified EWT (MEWT) method via data-driven adaptive Fourier spectrum segment for mechanical fault diagnosis is developed in this literature.

The main consideration of this paper focuses on a development of data-driven adaptive spectrum segment method to perform MEWT. Scale-space representation is an effective method to extract partition information from complicated Fourier spectrum of a practical signal by inner production [35]. In the MEWT method, boundaries are initially determined by local minima of scale-space representation with a pre-determined scale parameter. With detected boundaries, the signal is decomposed into a set of mono-components potentially carrying fault information. Hilbert transform is then applied to mono-components to extract modulation information. Next, mono-components are merged into a few empirical modes based on correlation coefficients of their envelope spectrums. The result will be used for identifying mechanical fault feature from noisy mechanical vibration signals.

The following of this paper is arranged as follows: The EWT theory is presented in Section 2. In Section 3, modified empirical wavelet transform is developed for mechanical fault diagnosis. In Section 4, a noisy mechanical fault simulation signal is formulated to validate the effectiveness of the proposed MEWT. Section 5 applies the proposed method to two examples of vibration signals from field tests, with comparison to the decomposition results of EMD and spectral kurtosis method. Finally, conclusions are drawn in Section 6.

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