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Adaptive variational mode decomposition method for signal processing based on mode characteristic

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A B S T R A C T

Variational mode decomposition is a completely non-recursive decomposition model, where all the modes are extracted concurrently. However, the model requires a preset mode number, which limits the adaptability of the method since a large deviation in the number of mode set will cause the discard or mixing of the mode. Hence, a method called Adaptive Variational Mode Decomposition (AVMD) was proposed to automatically determine the mode number based on the characteristic of intrinsic mode function. The method was used to analyze the simulation signals and the measured signals in the hydropower plant. Comparisons have also been conducted to evaluate the performance by using VMD, EMD and EWT. It is indicated that the proposed method has strong adaptability and is robust to noise. It can determine the mode number appropriately without modulation even when the signal frequencies are relatively close.

1. Introduction

There are a lot of unstable signals in nature, which usually contain important information. As an important method to deal with non-stationary signals, signal decomposition can decompose a complex signal into several regular simple modes, which can be easily analyzed in the time and frequency domain. In 1998, Huang et al. [1] proposed the empirical mode decomposition (EMD) algorithm. This algorithm is not limited by the Heisenberg uncertainty principle and can decompose signal recursively with a high frequency resolution according to the characteristics of the signal itself without the need to master prior knowledge. Many scholars have carried out comprehensive researches on EMD and have developed many related methods, such as Ensemble Empirical Mode Decomposition (EEMD) [2] and Local Mean Decomposition (LMD) [3]. However, these methods are based on recursive decomposition, which could lead to the accumulation of error gradually. In addition, they are sensitive to noise and sampling frequency [4]. In 2013, Gills proposed a novel approach called Empirical Wavelet Transform (EWT) [5]. It can design an appropriate wavelet filter bank adaptively according to the processed singal. For the purpose of stronger robustness of EWT in case of heavy noise, Chen et al. applied wavelet spatial neighboring coefficient denoising with data-driven threshold to increase the Signal to Noise Ratio (SNR) before EWT [6]. Bhattacharyya et al. studied multivariate extension of EWT on multivariate multicomponent synthetic signal as well as on multivariate electroencephalogram (EEG) of Children's Hospital Boston-Massachusetts Institute of Technology scalp EEG database [7]. In order to avoid presetting the number of modes in EWT, Gills et al. presented a simple parameterless scale-space method to find meaningful modes in histograms [8]. Zheng et al. proposed the adaptive parameterless EWT (APEWT) method in

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association with quadrature derivative based normalized Hiblert transform [9]. Pan et al. developed a modified EWT (MEWT) method via data-driven adaptive spectrum segment and improved it further by modifying the nonlocal means algorithm [10,11].

In 2013, Dragomiretskiy et al. proposed a novel completely non-recursive variational mode decomposition (VMD) method [12]. This method transforms mode decomposition into variational solution problem and utilizes the alternating direction multiplier method to optimize. In the process of optimization, an ensemble of modes with band-limited feature is obtained. VMD is essentially a set of adaptive Wiener filter bank. It can separate the modes with different center frequencies. Wang et al. conducted a comparison to evaluate the effectiveness of identifying the rubbing-caused signatures by means of VMD, EMD, EEMD and EWT in [13]. Zhang et al. successfully extracted the principal modes for fault diagnosis in rolling bearings signal of a multistage centrifugal pump by using VMD [14]. The results of the rubbing signals show that the multiple features can be better extracted with the VMD. However, VMD has a significant drawback, that is, the need to offer the number of modes in advance. If the preset mode number is unreasonable, it may induce the loss of important modes or produce mixing signal components. At present, in the application of VMD for signal analysis, the main approach to determine the appropriate mode number K is the central frequency observation method, namely, one should preset a number of values of K to run VMD several times repeatedly, and then observes the results of all trials to choose the appropriate K value [15]. This approach requires manual judgments and experience, which makes it cumbersome in an application and greatly limits the VMD's adaptability. In order to overcome the drawback, some studies have been conducted. In [16], when dealing with the noise in a biomedical image by utilizing VMD, the mode number is consistent with that of EMD. This is obviously not convenient for VMD. Liu et al. introduced the criterion of mutual information to improve the iterative stopping conditions in [17]. Tang et al. took the ratio of residual energy to original signal energy as optimization index in [18]. The final mode number was determined when the ratio was less than the threshold. The above two methods in [17] and [18] both regard the quantitative relationship between the residual and the original signal as an indicator, but dose not take into account the characteristics of the signal component, which easily lead to mode mixing. Wang used chaos particle swarm optimization algorithm to optimize the mode number and penalty parameter of VMD in [19]. Although this method can obtain the appropriate parameter value, it is inefficient because it needs to perform a large number of trials iteratively. Mou et al. regarded the ratio of frequencies between neighboring modes obtained by VMD as an indicator to automatically determine the mode number [20]. This method avoids the mode mixing between the modes, but the internal mode mixing in one mode has not been considered. Liu et al. designed a criterion based on detrended fluctuation analysis (DFA) to select the decomposition level in [21]. Li proposed independence-oriented VMD method, which adaptively chose the initial mode number and the most suitable mode number by peak searching and similarity principle in [22].

In this paper, a method called Adaptive Variational Mode Decomposition (AVMD) was presented to automatically determine the mode number based on the characteristics of intrinsic mode function. This method judges the VMD's decomposition results in the guide of a series of indicators including permutation entropy, extreme value in the frequency domain, kurtosis criterion and energy loss coefficient, etc. After the judgment, AVMD can adjust the mode number K and analyze the signal again until the appropriate K value is obtained. Different kinds of signals are processed by AVMD such as noise-free signal, noisy signal, a signal with close harmonics in frequency, measured signals in the hydropower plant. The results indicate that AVMD method has strong adaptability and is robust to noise. In addition, the method can automatically determine the mode number accurately even when the frequency spacing is relatively small in a signal.

The rest of the paper is organized as follows: Section 2 reviews the concept of VMD briefly and introduces the conceptions and characteristic of efficient mode function (EMF) and mode function with noise (MFN). Then the indicators are discussed to distinguish EMF, MFN and noise. Based on the above theories, we present the implementation step of the proposed AVMD. In Section 3, AVMD is employed to conduct the analysis of simulation signals. The results are compared to the ones analyzed by VMD, EMD and EWT. Section 4 contains detection and separation of measured signals calculated by AVMD, EMD and EWT. Discussion and conclusion are presented in Section 5.

2. The principle of AVMD

2.1. Variational mode decomposition

The intrinsic modal function (IMF) of variational mode decomposition is defined as an amplitude-modulated-frequency-modulated (AM-FM) signal [12]. The kth mode $u_k(t)$ is written as:

$$u_k(t) = A_k(t)\cos(\phi_k(t)) \tag{1}$$

where $A_k(t)$ is the instantaneous amplitude; $\phi_k(t)$ is the instantaneous phase, and its derivative $\omega_k(t) = \phi'_k(t)$ is the instantaneous frequency.

For each mode $u_k(t)$, VMD constructs the analytic signal by means of Hilbert transform and calculates the unilateral frequency spectrum. Then the mode's spectrum is shifted to baseband according to displacement property of Fourier transform. After that, the bandwidth is estimated through the H^1 Gaussian smoothness. The goal of optimization is to minimize the sum of the spectral widths of all the IMFs as follows: