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Complete ensemble local mean decomposition with adaptive noise and its application to fault diagnosis for rolling bearings

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ABSTRACT

Mode mixing resulting from intermittent signals is an annoying problem associated with the local mean decomposition (LMD) method. Based on noise-assisted approach, ensemble local mean decomposition (ELMD) method alleviates the mode mixing issue of LMD to some degree. However, the product functions (PFs) produced by ELMD often contain considerable residual noise, and thus a relatively large number of ensemble trials are required to eliminate the residual noise. Furthermore, since different realizations of Gaussian white noise are added to the original signal, different trials may generate different number of PFs, making it difficult to take ensemble mean. In this paper, a novel method is proposed called complete ensemble local mean decomposition with adaptive noise (CELMDAN) to solve these two problems. The method adds a particular and adaptive noise at every decomposition stage for each trial. Moreover, a unique residue is obtained after separating each PF, and the obtained residue is used as input for the next stage. Two simulated signals are analyzed to illustrate the advantages of CELMDAN in comparison to ELMD and CEEMDAN. To further demonstrate the efficiency of CELMDAN, the method is applied to diagnose faults for rolling bearings in an experimental case and an engineering case. The diagnosis results indicate that CELMDAN can extract more fault characteristic information with less interference than ELMD.

1. Introduction

Rolling bearings are the core components in both transmission and power systems of mechanical equipment. Fault diagnosis of rolling bearings is of vital significance for ensuring normal systematic operation [1–3]. Due to the high relevance between vibration signals and bearing running states, vibration analyze based on signal processing methods are widely used in fault diagnosis field [4,5]. The vibration analysis methods can be basically divided into three categories: time-domain, frequency-domain and time–frequency methods. In the case of non-stationary and nonlinear signals, both time-domain and frequency-domain methods are generally insufficient [6]. Over the past decade, time–frequency methods, such as Wigner–Ville distribution (WVD) [7] and wavelet transform (WT) [8,9], have been introduced to deal with non-stationary and nonlinear signals in the fault diagnosis field. However, inherent cross-interference item hinders the usefulness of WVD [10]. Wavelet basis functions and decomposition levels must be empirically chosen in analyzing practical signals,

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which makes WT non-adaptive [11]. Thus, there is an urgent need for adaptive non-stationary and nonlinear signal processing methods in the fault diagnosis field.

Huang et al. [12] originally proposed empirical mode decomposition (EMD) as an adaptive time–frequency method to decompose any complicated signal into a set of intrinsic mode functions (IMFs). However, when intermittent components exist in the signals, mode mixing will occur affecting the performance of EMD. Wu and Huang [13] developed the ensemble empirical mode decomposition (EEMD), which resolves the mode mixing problem, associating EMD with the help of added Gaussian white noise. Even though EEMD alleviates the mode mixing issue to some degree, it also introduces two new problems: (1) The modes produced by EEMD contain the residual noise and a large number of ensemble trials are required to eliminate the added noise, which are time-consuming. (2) While different realizations of Gaussian white noise are added to the original signal, different trials may generate different number of modes, making it difficult to take ensemble mean. Complementary ensemble empirical mode decomposition (CEEMD) method efficiently eliminates the residual noise via pairs of complementary (positive and negative) added white noise, using fewer ensemble trials compared to EEMD [14]. Still, the second problem remains unsolved. More recently, Torres et al. [15] proposed the complete ensemble local mean decomposition with adaptive noise (CEEMDAN) method which solves both of the problems. Colominas et al. [16] continued to improve CEEMDAN to solve the problem that some "spurious" IMFs may appear in the early decomposition stages. Due to the advantages of CEEMDAN, Lei et al. [17] employed it to diagnose fault for rolling bearings and achieved satisfactory results.

Smith [18] originally put forward the local mean decomposition (LMD) method and discussed its advantages over EMD in their applications to electroencephalogram signals. As an adaptive decomposition method for nonlinear and nonstationary signals, LMD has been applied to fault diagnosis for many years. Initially, Wang et al. [19] attempted to improve the performance of LMD focusing on the strategies for boundary data points processing and determination of step size of moving average. Comparing EMD and LMD for fault diagnosis, it was concluded that LMD is more suitable and performs better than EMD for incipient fault detection [20]. Chen et al. [21] developed a demodulating approach based on LMD and employed it to mechanical fault diagnosis. Further, Cheng et al. [22] tested the effectiveness of the LMD method in the fault diagnosis of rotating machinery. The second generation wavelet transform and LMD were combined by Liu et al. [23], and adopted for analyzing real engineering data obtained from a locomotive rolling bearing. Guo et al. [24] reduced the end effects of LMD by extending the waveform, based on spectral coherence. However, mode mixing resulting from intermittent signals is an annoying problem of LMD as well. Taking the same strategy as EEMD, Yang et al. [25] developed the ensemble local mean decomposition (ELMD) method to deal with the mode mixing problem in LMD, and indicated that ELMD is more efficient in local rub-impact fault diagnosis than EEMD. Subsequently, Sun et al. [26] combined ELMD and high-order ambiguity function to locate the natural gas leakage. Wang et al [27] developed a time–frequency analysis method based on ELMD and fast kurtogram to diagnose rotating machinery fault. Aiming at enhancing the performance of ELMD, Zhang et al. [28] optimized the parameters of ELMD, including noise amplitude, noise bandwidth, and ensemble number based on relative root-mean-square error and signal-to-noise ratio (SNR). However, ELMD still suffers from the aforementioned problems as EEMD.

Inspired by the previous studies presented in [15,16], we propose a complete ensemble local mean decomposition with adaptive noise (CELMDAN) method to address the existing problems of ELMD in this paper. A product function (PF) of white noise pre-processed by LMD with adaptive amplitude is added at every decomposition stage for each trial. Moreover, a unique residue is obtained after separating each PF, and the obtained residue is used as input for the next stage. As a result, the proposed method provides modes with less residual noise and better spectral separation, requires fewer sifting iterations, and solves the final average problem compared to ELMD. In this way, the decomposition is complete and adaptive.

The paper is arranged as follows. In Section 2, LMD and ELMD are briefly introduced. Section 3 gives a description of the proposed method, and a comparative study of the ELMD, CEEMDAN, and CELMDAN methods is presented by analyzing two simulated signals. Section 4 is devoted to the applications of CELMDAN in fault diagnosis for rolling bearings, and provides a comparison between ELMD and CELMDAN. The main conclusions are outlined in Section 5.

2. Background theory

2.1. LMD method

LMD deems any signal as a superposition of amplitude-modulated-frequency-modulated (AM-FM) components such that:

$$x(t) = \sum_{j=1}^{J} a_j(t) cos\varphi_j(t) \tag{1}$$

It adaptively decomposes the signal into a set of principal "modes", the so-called PFs. Each PF is the product of an amplitude envelope signal and a pure frequency modulated signal. Given a signal $x(t)$, the LMD algorithm is briefly described as Algorithm 1.