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An adaptively fast ensemble empirical mode decomposition method and its applications to rolling element bearing fault diagnosis

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ABSTRACT

Ensemble empirical mode decomposition (EEMD) represents a significant improvement over the original empirical mode decomposition (EMD) method for eliminating the mode mixing problem. However, the added white noises generate some tough problems including the high computational cost, the determination of the two critical parameters (the amplitude of the added white noise and the number of ensemble trials), and the contamination of the residue noise in the signal reconstruction. To solve these problems, an adaptively fast EEMD (AFEEMD) method combined with complementary EEMD (CEEMD) is proposed in this paper. In the proposed method, the two critical parameters are respectively fixed as 0.01 times standard deviation of the original signal and two ensemble trials. Instead, the upper frequency limit of the added white noise is the key parameter which needs to be prescribed beforehand. Unlike the original EEMD method, only two high-frequency white noises are added to the signal to be investigated with anti-phase in AFEEMD. Furthermore, an index termed relative root-mean-square error is employed for the adaptive selection of the proper upper frequency limit of the added white noises. Simulation test and vibration signals based fault diagnosis of rolling element bearing under different fault types are utilized to demonstrate the feasibility and effectiveness of the proposed method. The analysis results indicate that the AFEEMD method represents a sound improvement over the original EEMD method, and has strong practicability.

1. Introduction

EMD is the core part of Hilbert–Huang transform (HHT), with which any given complicated signal can be adaptively decomposed into a series of intrinsic mode functions (IMFs) based on the local characteristic time scales of the original signal [1]. With considering the favorable performance of EMD in nonlinear and non-stationary signals processing, it has found wide-ranging applications in many fields, such as mechanical fault diagnosis [2–4], image processing [5], crack detection and monitoring [6] and speech signal analysis [7]. However, there still exist some open drawbacks in EMD that are still underway [8,9]. One of the major disadvantages is the phenomenon of mode mixing, which is caused by intermittent signals or noise components. The significant hazard of the mode mixing problem is that it can lead the physical meaning of

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individual IMF component unclear or distorted [10]. To settle this problem and enhance the decomposition performance of EMD, a noise assisted data analysis method called ensemble empirical mode decomposition (EEMD) was originally proposed by Wu and Huang [9].

The EEMD method was inspired by the dyadic filter bank property of EMD when it was applied to white noises. By using EEMD, the composed components of the signal with different scale can be automatically projected onto appropriate uniform reference frame established by the added white noises, and then the mode mixing problem can be eliminated. Admittedly, EEMD represents a significant improvement over the original EMD method and has been applied in many fields as a more mature time-frequency analysis method [11–15]. However, the added white noise generates some tough problems including the contamination of the residue noise in the signal reconstruction, the high computational cost and the determination of the two critical parameters (the amplitude of the added white noise and the number of ensemble trials). To settle these problems, a certain number of countermeasures and improvements were reported in the corresponding literatures [12,16–19].

To eliminate the contamination of the residue noise in the signal reconstruction, Yeh et al. [16] proposed a novel noise assisted analysis method called complementary EEMD (CEEMD), in which the white noises are added in pairs with plus and minus signs to the targeted signal. As the CEEMD method performs well in eliminating the contamination of the residue noise and it would not consume extra computational time, this novel noise-assisted data analysis method is recommended as a standard form for the original EEMD method. Although the contamination of the residue noise can be removed exactly by the CEEMD method, a larger number of ensemble trials are also necessary to yield the IMFs with the similar root-mean-square (RMS) noise as EEMD, which could lead high time consumption. In addition, how to choose proper parameters is also a tough problem that needs to be settled for CEEMD.

To reduce the computational complexity, a certain degree of improvement in terms of computational efficiency of EEMD was obtained in literature [17] by restricting the frequency band of the added white noises. Although the computation time can be reduced to some extent via this method, this improvement is not significant. In literature [18], an improved noise-assisted method called partly ensemble empirical mode decomposition (PEEMD) was proposed to reduce the computational cost by performing the original EMD method on the residue signal which contains no intermittent and noise components. Although a significant improvement of computational efficiency can be obtained by PEEMD, the determination of the permutation entropy threshold is not adaptive and difficult. In literature [19], a significant reduction for the computational complexity in EEMD can be obtained by over-sampling the original signal to reduce the ensemble trials. By using EEMD, for the weakly sampled signal, it always needs a relatively large amplitude noise to intervene the extrema distribution of the targeted signal, which could lead high computation time. With regard to the over-sampling signal, the improvement of computational efficiency can be obtained by reducing the ensemble trials with addition of a minor-amplitude noise. But if the sampling frequency of the signal is too large, it can easily increase the burden of data collection and data storage in the phase of signal acquisition. Moreover, in most instances, the sampling frequency of the given signal cannot be changed.

With the generation of EEMD, an empirical method was previously proposed for the selection of the two critical parameters. In literature [9], the amplitude of the added white noise and the ensemble number were set to empirical value. But it is not always suitable for any case and should be adjusted according to the characteristics of the original signal. Recently, some performance index was utilized for the selection of the two critical parameters. In literature [17], an index termed the correlation coefficient between the IMF and the composed component of the original signal was employed to find the proper number of ensemble trials. Žvokelj et al. [13] presented the signal-to-noise ratio (SNR) as a performance index to select the proper noise amplitude. However, the parameters selection by these two methods is based on the assumption that the prior knowledge of the original signal is clear. Hence they are not suitable for practical signals. Niazy et al. [20] presented a new index termed relative root-mean-square error (RRMSE) to evaluate the decomposition performance of EEMD under different noise levels to find the proper noise level, where the parameter selection is adaptive. However, in literature [20], the detailed procedures for the selection of the proper noise level based on RRMSE are not given. Fortunately, Guo et al. [12] presented a more detailed description about the relative RMSE for the selection of the appropriate noise level, where the results demonstrated the effectiveness of the evaluation index RRMSE. In addition, to further improve the decomposition performance, an adaptive EEMD (AEEMD) method was proposed by Lei et al. [21]. In AEEMD, it mainly concentrates on the adaptive selection of the sifting number and the noise amplitude during the decomposition procedure. But for the initial value of the ensemble number and the noise amplitude, the empirical approach was performed.

Essentially, in EEMD, the aim of adding white noise is to homogenize the extrema distribution of the original signal for eliminating the mode mixing problem. Ideally, it seems that the smaller the noise amplitude can be the better. But if the noise amplitude is too small, then it could not lead the enough change of extrema distribution that EMD relies on. Hence the amplitude of the added white noise should not be too small [22]. Under this condition, a few hundred of ensemble trials are necessary for eliminating the effect of residue noise, which can lead to high computational cost. According to the above analysis, the fact has been found that the computational time of EEMD mainly is consumed on eliminating the residue noise caused by the added white noises.

For vibration or noise signals, the extrema density (average number of extrema per unit of length) represents the frequency of signal. If the frequency is higher, the extrema density is higher, and vice versa. By increasing the frequency, the minor amplitude noise can cause enough change of extrema distribution and make the extrema distribution more homogeneous. With above analysis, an adaptively fast EEMD (AFEEMD) method combined with CEEMD is proposed in this paper for the treatment of the above three problems. In AFEEMD method, a significant improvement in terms of