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Integrated ensemble noise-reconstructed empirical mode decomposition for mechanical fault detection

Jing Yuan [a,*], Feng Ji [b], Yuan Gao [a], Jun Zhu [a], Chenjun Wei [a], Yu Zhou [a]

[a] Shanghai Radio Equipment Institute, Shanghai 200090, PR China
[b] Shanghai Aerospace Electronic Technology Institute, Shanghai 201109, PR China

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ABSTRACT

A new branch of fault detection is utilizing the noise such as enhancing, adding or estimating the noise so as to improve the signal-to-noise ratio (SNR) and extract the fault signatures. Hereinto, ensemble noise-reconstructed empirical mode decomposition (ENEMD) is a novel noise utilization method to ameliorate the mode mixing and denoised the intrinsic mode functions (IMFs). Despite the possibility of superior performance in detecting weak and multiple faults, the method still suffers from the major problems of the user-defined parameter and the powerless capability for a high SNR case. Hence, integrated ensemble noise-reconstructed empirical mode decomposition is proposed to overcome the drawbacks, improved by two noise estimation techniques for different SNRs as well as the noise estimation strategy. Independent from the artificial setup, the noise estimation by the minimax thresholding is improved for a low SNR case, which especially shows an outstanding interpretation for signature enhancement. For approximating the weak noise precisely, the noise estimation by the local reconfiguration using singular value decomposition (SVD) is proposed for a high SNR case, which is particularly powerful for reducing the mode mixing. Thereinto, the sliding window for projecting the phase space is optimally designed by the correlation minimization. Meanwhile, the reasonable singular order for the local reconfiguration to estimate the noise is determined by the inflection point of the increment trend of normalized singular entropy. Furthermore, the noise estimation strategy, i.e. the selection approaches of the two estimation techniques along with the critical case, is developed and discussed for different SNRs by means of the possible noise-only IMF family. The method is validated by the repeatable simulations to demonstrate the synthetical performance and especially confirm the capability of noise estimation. Finally, the method is applied to detect the local wear fault from a dual-axis stabilized platform and the gear crack from an operating electric locomotive to verify its effectiveness and feasibility.

1. Introduction

Mechanical fault detection has received considerable attentions from researchers during the past decades, because of the maintenance pressure for reducing costly breakdowns and safety hazards. For the purpose, the vibration based signal processing methods using variational mode decomposition [1], matching pursuit [2], sparsity denoising [3], multiwavelets [4]

* Corresponding author.
E-mail address: yuanjing_802@163.com (J. Yuan).

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and so on are investigated recently. These methods are almost by the approaches to suppressing the noise for improving the signal-to-noise ratio (SNR) to enhance the fault signatures. Despite the nice performance of these methods, one of the drawbacks is revealed to be the overkilling of fault symptoms, leading to the diagnostic failure.

Different from the traditional noise suppression methods, the noise utilization methods are a new branch of fault feature extraction and identification by the means of enhancing, adding or estimating the noise. Hereinto, ensemble empirical mode decomposition (EEMD) proposed by Wu and Huang [5] is a typical noise utilization method originated from empirical mode decomposition (EMD) [6,7] to address the mode mixing problem. As a promising adaptive time-frequency tool, EEMD-based analysis methods and practices have continued to improve for mechanical condition monitoring and fault diagnosis [8–14]. EEMD sifts the observed data augmented by additional white noises and defines an ensemble mean intrinsic mode functions (IMFs) as the results. Although the additional noises cancel each other out in the ensemble mean of enough trails, the noise component inherent in the observation may not be eliminated for enhancing the fault signatures to identify the potential faults from mechanical equipments.

As a novel noise utilization method, ensemble noise-reconstructed empirical mode decomposition (ENEMD) inspired by denoising [15], is proposed by Yuan and He et al. to ameliorate the mode mixing and denoise IMFs for fault detection [16], in which the ensemble mean IMFs are sifting by the reconstructed signals using the estimated noise inherent in the observation. To improve the mode mixing, the different noise renderings estimated and resampled not only assist in alleviating the signal intermittency, but also help to project different signal scales onto their corresponding IMFs. Meanwhile, the undesirable noise component is eliminated from the signal by the ensemble mean approach given enough trails, which is powerful in fault signature enhancement. Subsequently, the noise estimation of ENEMD is developed using the neighboring coefficient denoising and then the improved ENEMD is introduced to Hilbert-Huang transform for weak time-frequency feature enhancement [17].

The noise estimation strategy is the significant issue concerned in ENEMD, in which the hard thresholding is performed on the chosen possible noise-only IMFs by the IMF-dependent threshold Tu, defined as

$$Tu = C\sqrt{2E\ln N} \tag{1}$$

where C is a constant factor, E and N are respectively the noise energy level and length of IMF. However, the noise estimation strategy suffers from the following major drawbacks. On one hand, the user-defined C influences the accuracy of noise estimation as well as the effect of final results. The artificial setup is according to the denoising demand and experimental experience. It is lack of the setup criteria and difficult to conduct in practice, leading to the non-adaptability and non-automation of the method. On the other hand, the weak noise is challenging to estimate because of the little amplitude of inherent noise. Thereby, the hard thresholding technique is sometimes powerless for a high SNR case, and also exists the discontinuity phenomenon. To solve the problems, integrated ensemble noise-reconstructed empirical mode decomposition (IENEMD) is proposed for mechanical fault detection. The main contributions of the papers are focused on: (1) Two noise estimation techniques are proposed to improve the precise of noise estimation in IENEMD. (2) In the first one, the minimax thresholding is introduced for estimating a low SNR signal. There is no parameter setup artificially, resulting in the adaptive and automatic noise estimation. (3) In the second one, the local reconfiguration using singular value decomposition (SVD) is developed for estimating a high SNR signal. The reconstructed phase space for SVD is designed using the sliding window, the width of which is determined by the correlation minimization. Furthermore, the reasonable singular order for local reconfiguration is selected by the inflection point of the increment trend of normalized singular entropy. (4) The noise estimation strategy for IENEMD, i.e. the selection rule of the two noise estimation techniques, is proposed according to the selection results of possible noise-only IMFs. Finally, the method is verified by the numerical simulations and fault detection on a dual-axis stabilized platform and an operating electric locomotive.

The rest structure of the paper is organized as follows. A brief description of ENEMD is reviewed in Section 2. The proposed method is given in Sections 3 and 4, including the two noise estimation techniques as well as the strategy. Section 5 explores simulations and engineering validations. Section 6 provides conclusions.

2. Summary of ENEMD

Originated from EMD, ENEMD is also an adaptive time-frequency signal processing method which could give meaningful interpretation for nonstationary or nonlinear processes. The basic theory of EMD such as the IMF definition and EMD algorithm used in the paper is not repeatedly reviewed here and referred to Ref. [6]. As we know, noise is ubiquitous in any measured signal encountered in practice. Without loss of generality, a measured signal $\{x(t), t = 1, \ldots, N\}$ is expressed by

$$x(t) = s(t) + n(t) \tag{2}$$

where $s(t)$ is the true noise-free component and $n(t)$ is the noise component. The algorithm of ENEMD is outlined as the following steps [16].

(1) Generate $\hat{n}(t)$ using the noise estimation strategy from $x(t)$, where the symbol ^ represents an estimation.
(2) Resample $\hat{n}(t)$ by the random permutation to achieve the jth noise rendering $\hat{n}_j(t)$.
(3) Reconstruct the noisy observation $\hat{x}_j(t)$ using