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A hybrid fault diagnosis method using morphological filter–translation invariant wavelet and improved ensemble empirical mode decomposition

Lingjie Meng [a,b], Jiawei Xiang [a,*], Yanxue Wang [b], Yongying Jiang [a], Haifeng Gao [a]

[a] *College of Mechanical and Electrical Engineering, Wenzhou University, Wenzhou 325035, PR China*
[b] *School of Mechanical and Electrical Engineering, Guilin University of Electronic Technology, Guilin 541004, PR China*

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Defective rolling bearing response is often characterized by the presence of periodic impulses, which are usually immersed in heavy noise. Therefore, a hybrid fault diagnosis approach is proposed. The morphological filter combining with translation invariant wavelet is taken as the pre-filter process unit to reduce the narrowband impulses and random noises in the original signal, then the purified signal will be decomposed by improved ensemble empirical mode decomposition (EEMD), in which a new selection method integrating autocorrelation analysis with the first two intrinsic mode functions (IMFs) having the maximum energies is put forward to eliminate the pseudo low-frequency components of IMFs. Applying the envelope analysis on those selected IMFs, the defect information is easily extracted. The proposed hybrid approach is evaluated by simulations and vibration signals of defective bearings with outer race fault, inner race fault, rolling element fault. Results show that the approach is feasible and effective for the fault detection of rolling bearing.

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1. Introduction

Rolling bearings cover a broad range of rotary machines and plays a crucial role in the modern manufacturing industry. The failures of rolling bearing can result in the deterioration of machine performance and it is significant to accurately and easily detect the existence and severity of a fault in the bearing. As the vibration signal carrying a great deal of information representing the mechanical equipment's health conditions, the use of vibration analysis has been established as the most common and reliable method of analysis in the field of condition monitoring and diagnostics of rotating machinery [1–4]. Additionally, the vibration signal is ordinarily non-stationary and non-linear, and the fault features are always immersed in heavy noise; therefore, the feature extraction of bearing fault signals is a relatively important problem. Conventional signal processing techniques, such as time-domain statistical analysis, Fourier transform, short-time Fourier transform (STFT), Wigner–Viller distribution (WVD), etc., are based on the assumption that the signals are stationary and linear [5–7], which is not in compliance with the actual situation. Wavelet transform (WT) has been a good choice to deal with the

* Corresponding author.
E-mail address: wxw8627@163.com (J. Xiang).

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non-stationary signals [8–11]. However, WT suffers from the following disadvantages, such as the appropriate selections of the base function and certain frequency bands with defect information.

Empirical mode decomposition (EMD) has been recently developed in fault diagnosis of rotating machinery [12–14]. EMD is based on the local characteristic time scales of a signal and could decompose the complicated signal into a set of complete and almost orthogonal intrinsic mode functions (IMFs) [15–20]. EMD is a self-adaptive signal processing method that can be applied to non-linear and non-stationary process perfectly. However, one of the major drawbacks of EMD is the mode mixing problem [21,22]. To alleviate this problem, ensemble empirical mode decomposition (EEMD) is developed by Wu and Huang [23]. However, in practical applications of EEMD, some problems need to be solved, e.g., the reducing of the narrowband impulses and random noises embedded in original signal, and the eliminating of the undesirable pseudo IMFs.

To reduce the narrowband impulses, the morphological filter has been widely used because of its adaptive and robust performance in restraining positive and negative impulse [24,25]. To reduce the random noises, the translation invariant wavelet denoising method can inhibit the pseudo-Gibbs phenomenon and the random noises effectively [26]. To extract the real components from the IMFs obtained by EEMD, Peng et al. [27] proposed a simple method which uses the correlation coefficients of IMFs and the original signal as a criterion. All the correlation coefficients will be compared with a hard threshold (a ratio of the maximal correlation coefficients). However, in practical applications, the criteria of the ratio have not been defined clearly. The too big or too small ratios will lead to the elimination of real components or the failure of removing the pseudo low-frequency components, respectively. Therefore, the more feasible and effective method for the selection of IMFs need to be developed necessarily.

For the above reasons, this paper presents a hybrid approach for the rolling bearing fault diagnosis. The combination of morphological filter and translation invariant wavelet is taken as the pre-filter process unit of EEMD. Then a new selection method integrating autocorrelation analysis with the first two IMFs having the maximum energies is proposed to eliminate the pseudo low-frequency components of IMFs. Applying the envelope analysis on the preserved real IMFs, the defect information is easy to be extracted. The paper is organized as follows. We briefly describe the fundamental theory of translation invariant wavelet and morphological filter in Sections 2.1 and 2.2, respectively. In Section 2.3, the combination of both methods is applied to a simulated signal to remove the narrowband impulses and random noises. The fundamental theory of EEMD and the proposed IMFs selection method is shown in Sections 3.1 and 3.2, respectively, and then a simulation analysis is carried out to validate the effectiveness of the selection method. In Section 4, the hybrid approach is verified using the vibration signals of defective bearings with outer race fault, inner race fault, and rolling element fault, respectively. Finally, the conclusions are drawn in Section 5.

2. Translation invariant wavelet and morphological filter

2.1. A brief introduction of translation invariant wavelet

The wavelet denoising method has been most commonly used, especially the soft-threshold denoising method [28]. However, the traditional wavelet methods may result in visual artifact on discontinuities of signals at some circumstances, namely pseudo-Gibbs phenomenon, which lead to location discontinuity. If applying the translation invariant wavelet, this drawback would be alleviated [26]. Briefly, the process can be summarized as follows:

Let $H_n = \{h | 0 \le h \le n\}$ denote the shift quantity, and S_h denote the circulant shift by h. For a signal $x(t)(0 \le t \le n)$, the time domain translation results by S_h are shown as

$$(S_h x)_t = x_{(t+h) mod\ n} \tag{1}$$

where *mod* represents the modulus after division. Since the circulant shift is invertible, the reverse shift $(S_h)^{-1}$ is represented by

$$(S_h)^{-1} = S_{-h} \tag{2}$$

If T represents the processing operation using the threshold denoising process, the final purified signal after a single shift processing is represented by

$$\hat{x} = S_{-h}(T(S_h x)) \tag{3}$$

where $\hat{x}$ is the final purified signal. Considering the contradiction that there may be several discontinuities in the signal, the best shift for one discontinuity might be the worst shift for another discontinuity. Therefore, the method of multiple average of circulant shift processing is usually adopted. The process is represented by

$$\hat{x} = Ave_{h \in H} S_{-h}(T(S_h x)) \tag{4}$$

where Ave is the average operation, H is the translation range and the biggest H is n.

However, according to the above description, the shift parameter h has not been explicitly defined. More precisely, it appears that all the possible values of the shift parameter h need to be considered but not necessary. In fact, Beylkin [29] has already given a rapid way to perform the translation invariant wavelet transform for any possible h. The wavelet coefficients set obtained on any odd shift parameter h is equal to those using only a single circulant shift, whereas the wavelet coefficients set obtained on any even shift parameter h is equal to those without shift. Therefore, we can calculate

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