Mechanical Systems and Signal Processing 52-53 (2015) 376–392

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

journal homepage: www.elsevier.com/locate/ymssp

Multiscale envelope manifold for enhanced fault diagnosis of rotating machines

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ARTICLE INFO

Article history:
Received 26 October 2013
Received in revised form
12 July 2014
Accepted 29 July 2014
Available online 22 August 2014

Keywords:
Multiscale envelope manifold
Continuous wavelet transform
Wavelet envelope
Manifold learning
Machinery fault diagnosis

ABSTRACT

The wavelet transform has been widely used in the field of machinery fault diagnosis for its good property of band-pass filtering. However, the filtered signal still faces the contamination of in-band noise. This paper focuses on wavelet enveloping, and proposes a new method, called multiscale envelope manifold (MEM), to extract the envelope information of fault impacts with in-band noise suppression. The MEM addresses manifold learning on the wavelet envelopes at multiple scales. Specifically, the proposed method is conducted by three following steps. First, the continuous wavelet transform (CWT) with complex Morlet wavelet base is introduced to obtain the wavelet envelopes at all scales. Second, the wavelet envelopes are restricted in one or more narrow scale bands to simply include the envelope information of fault impacts. The scale band is determined through a smoothness index-based (SI-based) selection method by considering the impulsiveness inside the power spectrum. Third, the manifold learning algorithm is conducted on the wavelet envelopes at selected scales to extract the intrinsic envelope manifold of fault-related impulses. The MEM combines the envelope information at multiple scales in a nonlinear approach, and may thus preserve the factual envelope structure of machinery fault. Simulation studies and experimental verifications confirm that the new method is effective for enhanced fault diagnosis of rotating machines.

1. Introduction

It is well-known that wavelet transform is an effective time-frequency analysis tool for non-stationary signals due to its merits of flexible time-frequency resolution and efficiency of computational implementation. It has been widely applied to the field of machinery fault diagnosis because the dynamic signal of rotating machine has the non-stationary property. The signal measured under complex working conditions also contains heavy noise, which may corrupt the features extracted by wavelet transform, so some denoising methods based on wavelet analysis have been explored [1–4]. However, those methods only aim to smooth the curves of original noisy signals, while the characteristic frequency of machinery fault cannot be directly obtained. This is because the fault-related periodic impulse is a modulator to the high natural frequencies of the machine [5]. To demodulate the impact impulses, some wavelet-based demodulation methods have been studied

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http://dx.doi.org/10.1016/j.ymssp.2014.07.021
0888-3270/

[6–10] and confirmed to outperform the conventional filter-based or FFT-based Hilbert transform [7,9]. However, the extracted envelope by those methods is either at a single scale or among a scale band, which still confronts the contamination of in-band noise.

The wavelet transform possesses the function of band-pass filter. Thus it can trim down the frequency components outside the cut-off frequencies, and hence improve the signal-to-noise ratio (SNR) of analyzed signal. However, the noise components contained in the passing band (i.e. in-band noise) are still retained, which may corrupt the extracted features. To get rid of the in-band noise, different methods have been studied by some researchers. Bozchalooi and Liang [11] introduced the spectral subtraction technique before wavelet filtering, through subtracting an optimized estimate of power spectral density (PSD) of background white noise from the PSD of measured signal and then reconstructing the denoised signal with the phase information of original signal. He et al. [12] proposed a soft-threshold method called sparse code shrinkage (SCS) after wavelet filtering to eliminate the non-Gaussian noise and enhance the impulsive features. However, the above methods both need a proper threshold to be selected, which indicates their complexity. Su et al. [13] used an enhanced autocorrelation envelope power spectrum based on extended Shannon entropy function to remove the low-magnitude interfering frequency components in the frequency domain also after wavelet filtering. But the residual noise after filtering is not eliminated in the time domain. Most recently, our group addressed manifold learning algorithm on the multiple time-frequency distributions (TFDs) or time-scale distributions (TSDs) of non-stationary signal to produce time-frequency manifold (TFM) or time-scale manifold (TSM) signature of machinery fault [14,15], and further demodulated the periodic impulses by ridge analysis technique [15,16]. By the TFM or TSM based methods, the fault-induced impulses can be enhanced and the in-band noise can be greatly suppressed at the same time. Nevertheless, the computational load for TFM or TSM learning is very heavy, because each dimension of the input data derives from the large 2-D time-frequency or time-scale matrix. This makes these methods not applicable in on-line signal processing. An efficient strategy is required to take advantage of the excellent nonlinear denoising effect of manifold learning and further improve the SNR.

To reach the goal mentioned above, we constructed the high-dimensional data for manifold learning from the envelopes demodulated by wavelet transform at multiple scales [17]. The dimension of an envelope is hugely smaller than that of a TSD matrix for an analyzed signal, so the computational efficiency is largely improved as compared to the TFM or TSM learning. This method extracts the fault-related impulses by nonlinearly combining the demodulated signals at different wavelet scales. Hence it could reflect the multiscale information and non-linearity of the machinery dynamic systems simultaneously. In this paper, the achieved result by this approach is called multiscale envelope manifold (MEM). Specifically, the MEM is produced by three following steps. First, the continuous wavelet transform (CWT) with complex Morlet wavelet base is introduced to analyze the non-stationary signal over the whole spectrum to obtain the wavelet envelopes at all scales. Second, the scale band with the information of interest is determined. Third, the manifold learning algorithm is employed to extract the envelope manifold from the wavelet envelopes at the selected multiple scales. The benefits of the MEM can be explained as follows. The background noise is a random distribution among the wavelet envelopes at the determined scale band, while the fault-related impulses appear along the whole selected band periodically. Therefore, the impulses of fault impacts can be considered as a manifold structure, which will be retained in the manifold learning, while the noise will be ignored in the output. Due to the special merits mentioned above, the new MEM signature can exactly expose the factual envelope information of modulated measured signal.

This paper further addresses some issues to enhance the performance of the MEM method. In this study, the critical point to generate a good result for the MEM is which scales should be selected. It is known that the envelope information of machinery fault is embedded in the resonance band of measured signal. In current literature different methods have been explored to adaptively select the band of interest. Ref. [17] selected the resonance scale band by simply evaluating the scale energies, which may be misled by the strong noise at some scales. The spectral kurtosis (SK) proposed by Dwyer [18] is another measure to estimate the frequency locations of impulsive features in a non-stationary signal [19]. Antoni et al. [20,21] combined the short-time Fourier transform (STFT) and SK and constructed the kurtogram to discover the optimal frequency band for the diagnosis of rotating machinery fault. Moreover, the merits of CWT and wavelet packet transform (WPT) have been utilized for improving the kurtogram to select the optimal frequency band [22–24]. In the above methods, the SK is applied to the time series obtained by a series of band-pass filters. Barszcz et al. [25] found that the application of SK in the envelope spectrum amplitudes of filtered signals is capable of detecting transients with smaller SNR, so the protrugram was constructed for the optimal band selection. Then Wang et al. [26] further proposed an enhanced kurtogram by measuring the SK of the power spectrum of the envelope of the signals extracted from wavelet packet nodes. Tse and Wang [27] also substituted the sparsity value for the SK in the enhanced kurtogram to form a new sparsogram for bearing fault diagnosis. The literatures [25–27] indicate that the impulsiveness of fault-related information in complex noise environment is more sensitive to be detected in the frequency domain. This can be explained by that the periodic impulses in time domain are converted to be some peaks consisting of the characteristic frequency and its harmonics in the spectrum; the peaks are more steep and less noise-interfered than the impulses. In this paper, the frequency-domain detection approach is also employed to select the scales corresponding to resonance frequency band carrying impulsive fault information. Specifically, the smoothness index (SI) defined as the ratio of the arithmetic mean to the geometric mean is employed to measure the impulsiveness of the power spectrum of wavelet coefficient Moduli achieved by CWT at each scale, because it has been proved that the SI is superior to the kurtosis in the measure of impulsiveness [11]. In this paper, we also explore the possibility that there will be more than one resonance scale bands to be selected by the proposed SI-based scale band selection method. Considering that the noise contents are less correlated among different resonance scale bands