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Exchanged ridge demodulation of time-scale manifold for enhanced fault diagnosis of rotating machinery

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ABSTRACT

The vibration or acoustic signal from rotating machinery with localized fault usually behaves as the form of amplitude modulation (AM) and/or frequency modulation (FM). The demodulation techniques are conventional ways to reveal the fault characteristics from the analyzed signals. One of these techniques is the time-scale manifold (TSM) ridge demodulation method with the merits of good time–frequency localization and in-band noise suppression properties. However, due to the essential attribute of wavelet ridge, the survived in-band noise on the achieved TSM will still disturb the envelope extraction of fault-induced impulses. This paper presents an improved TSM ridge demodulation method, called exchanged ridge demodulation of TSM, by combining the benefits of the first two TSMs: the noise suppression of the first TSM and the noise separation of the second TSM. Specifically, the ridge on the second TSM can capture the fault-induced impulses precisely while avoiding the in-band noise smartly. By putting this ridge on the first TSM, the corresponding instantaneous amplitude (IA) waveform can represent the real envelope of pure faulty impulses. Moreover, an adaptive selection method for Morlet wavelet parameters is also proposed based on the smoothness index (SI) in the time-scale domain for an optimal time-scale representation of analyzed signal. The effectiveness of the proposed method is verified by means of a simulation study and applications to diagnosis of bearing defects and gear fault.

1. Introduction

The vibration or acoustic signals from rotating machinery contain rich information of health condition for diagnosis. When a localized defect occurs, the signal will perform as the form of amplitude modulation (AM) and/or frequency modulation (FM). The fault dynamic characteristic information is usually hidden in the envelope of this kind of signals. Hence, some demodulation techniques have been proposed to reveal the fault characteristic frequency from the vibration/acoustic signals. The Hilbert transform is a traditional enveloping technique. But it is a linear integral operation based on fast Fourier transform with a long data length requirement [1–3], which may lead to energy leakage and low adaptability to local feature of a signal. The energy separation algorithm (ESA) is another popular demodulation method in the field of machinery fault diagnosis in recent years [4–8]. As a data driven algorithm based on a nonlinear differential operation called Teager–Kaiser energy operator (TKEO), it is adaptive to the local characteristics of a non-stationary signal. However, the ESA

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requires that the analyzed signal should be mono-component and in narrow band [7], and it is sensitive to noise [8]. The above two methods are time-domain demodulation techniques. The wavelet-based demodulation methods are demodulation techniques in the time–frequency domain by using the wavelet transform [9–14], thus they have excellent time–frequency localization property. Among them, the wavelet ridge demodulation approach concerns main energy on the time-scale distribution (TSD) after continuous wavelet transform (CWT) for an AM–FM signal [15], which can obtain the instantaneous frequency (IF) information of FM part and instantaneous amplitude (IA) information of AM part simultaneously [14]. For all the methods above, there exists a tough challenge in practical fault diagnosis of rotating machinery working in complex environment. That is the removal of in-band noise.

The conventional filtering method can trim down the frequency components outside the cut-off frequencies, and thus improve the signal-to-noise ratio (SNR) of analyzed signal, whereas the noise among the passed frequency band (i.e. in-band noise) is still retained. To get rid of the in-band noise, Bozchalooi and Liang [17] introduced the spectral subtraction technique by subtracting a preset estimate of power spectral density (PSD) of background white noise from the PSD of measured signal before wavelet filtering. He et al. [18] proposed a soft-threshold method named sparse code shrinkage (SCS) to eliminate the non-Gaussian noise after wavelet filtering. Su et al. [19] used an enhanced autocorrelation envelope power spectrum based on extended Shannon entropy function to remove the low-magnitude frequency components of the wavelet-filtered signal directly in the frequency domain. The above methods deal with the in-band noise either in the time domain [18] or in the frequency domain [17,19]. Most recently, our group proposed a new ridge demodulation method, called time-scale manifold (TSM) ridge demodulation, by combining the wavelet ridge and nonlinear manifold learning, in order to suppress the in-band noise and enhance the impact impulses [16]. This method focuses on the time–frequency domain and shows encouraging results for machinery fault diagnosis. However, there are still some issues that remain to be addressed to further enhance the performance of the TSM ridge demodulation method.

The first issue that this paper addresses is on the TSM learning technique. The TSM is to learn an intrinsic nonlinear time-scale structure on a general TSD. As for TSD, the basic wavelet plays a key role in feature extraction of various signals. The Morlet wavelet is widely used in machinery fault diagnosis for its similarity to the fault-associated impulses. To choose proper parameters of Morlet wavelet, different methods have been explored. The Shannon entropy is the most common method. In order to obtain the best time-scale resolution, Lin and Qu [20] and Hai et al. [21] applied the Shannon entropy on wavelet coefficients of the TSD to select the optimal shape factor of real Morlet wavelet. Nikolaou and Antoniadis [13] further combined the Shannon entropy and a magnification factor criterion to optimize the parameter of complex shifted Morlet wavelet family. Lardies [22] also used the Shannon entropy on the energies of specific scales after the CWT to select the shape factor of the modified complex Morlet wavelet. In addition, Su et al. [19] set the Shannon entropy as the fitness function of Genetic algorithm to search for the optimal parameters of complex Morlet wavelet filter. Apart from Shannon entropy, kurtosis was also used as an indicator for the complex Morlet wavelet filter optimization [18]. Moreover, Bozchalooi and Liang [17] found that the smoothness index (SI) outperforms the kurtosis as an indicator of impulsiveness, so it was introduced for selection of the shape factor of complex Morlet wavelet after the CWT at one selected scale. For a conventional complex Morlet wavelet, there are two parameters, center frequency and bandwidth (i.e. shape factor). The above literatures focus on either selecting bandwidth for Morlet wavelet or choosing center frequency and bandwidth for the design of Morlet wavelet filter. However, there is no method that addresses selecting both center frequency and bandwidth of complex Morlet wavelet simultaneously for achieving the optimal time-scale representations of different faulty signals.

The second issue which is also a very important one to be addressed in this study is how to further improve the effect of in-band noise removal for the TSM ridge demodulation technique. Although the in-band noise can be greatly suppressed by manifold learning in the TSM technique, there are still part of them being more or less involved in the final result. This is due to the essential attribute of ridge points that they are the local maxima on the TSM not only at the time when fault impacts happen but also at the intervals between them. This study conducts a further exploration being motivated by an interesting phenomenon that the fault-related impulses are both convex upward in the first two TSMs while the noise is in the opposite directions. The similar phenomenon is also found in Ref. [23] when constructing a synthetic time–frequency manifold (TFM) signature for machine health pattern. Specifically, the top two TSMs indicate different properties. The first TSM shows the noise suppression property while the second one displays the noise separation merit. Therefore, it is expected to combine these two benefits to enhance the performance of in-band noise removal, and thus further enhance the performance of the TSM ridge demodulation technique.

In summary, aiming to enhance the performance of ridge demodulation technique in fault diagnosis of rotating machinery, this paper explores an improvement of the TSM ridge demodulation method. Specifically, the SI is first employed as an indicator for the measurement of impulsiveness of signal TSD, in order to select the optimal parameters of complex Morlet wavelet adaptively for various signals to be analyzed. After learning the TSM, the envelope information of faulty signal is obtained by extracting the IA from the first TSM along the ridge of the second TSM. In other words, the ridge of the first TSM is exchanged with the ridge of the second TSM in the improved TSM ridge demodulation. Thus the improved method is named exchanged ridge demodulation of TSM. There are three advantages for the proposed approach: (a) the wavelet parameters are adaptively selected; (b) the merits of TSM are kept; and (c) the in-band noise is avoided in the time-scale domain. Therefore, the achieved IA waveform can represent the factual envelope of analyzed signal with fault information. The fault characteristic frequency can be finally identified by spectral analysis of the demodulated result. The effectiveness of the new method is verified by means of simulation and experimental studies on fault diagnosis of rotating machinery.