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A new rotating machinery fault diagnosis method based on local oscillatory-characteristic decomposition

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ABSTRACT

A new self-adaptive time-frequency analysis method named local oscillatory-characteristic decomposition (LOD) is introduced. This method is based on local oscillatory characteristics of signal itself, and it uses kinds of mathematical operations such as differential, coordinate domain transform and piecewise linear transform to decompose the signal into a series of mono-oscillatory components (MOC) whose instantaneous frequency has physical meanings. Each of MOC represents a kind of oscillatory characteristic of the original signal, and thus reflects the intrinsic characteristics of the original signal, so the LOD method is particularly suitable for processing non-stationary signals. After illustrating the decomposition principle of LOD in detail, the LOD is compared with the empirical mode decomposition (EMD) and local mean decomposition (LMD) by analyzing simulation signals. The results show the superiority of LOD method. Meanwhile, aiming at the multi-component modulated characteristic of gear and roller bearing fault vibration signals, the envelope analysis based on LOD is applied to gear and roller bearing fault vibration signals analysis. Analytical results from experimental signal and real signal demonstrate that the new diagnosis approach based on LOD can identify gear and roller bearing work condition accurately and effectively.

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1. Introduction

The key to fault diagnosis of rotating machinery is to extract fault characteristics from mechanical vibration signals [1,2]. However, mechanical vibration signals are characterized by non-stationary and low signal-to-noise ratio (SNR), and mechanical systems are characterized by nonlinearity. These make the state characteristic information of machinery contained in vibration signals is difficult to exhibit directly [3,4]. Hence, an appropriate signal processing method needs to be identified for the processing of signals. The time-frequency analysis method is deemed as the existing most effective methodology to process non-stationary and nonlinear signals. Typical time-frequency analysis methods comprise short-time Fourier transform, Wigner–Ville distribution and wavelet transform, all of which have a common deficiency of lacking self-adaptive [5]. The empirical mode decomposition (EMD) is a self-adaptive time-frequency analysis method proposed by N.E. Huang. EMD does not require any priori knowledge, but entirely based on the time-scale characteristics of the signal itself to decompose the signal into a number of intrinsic mode functions (IMFs). Then performing Hilbert transform to each IMF, and the corresponding instantaneous amplitude and instantaneous frequency can be calculated. Thus, the complete time-frequency distribution of the original signal can be obtained [5]. EMD provides a brand-new idea for the self-adaptive time-frequency analysis, which remains the method of self-adaptive time-frequency analysis in a real sense. Therefore, it has been widely applied in various fields since it is proposed [6–10]. However, theoretically EMD suffers from a number of issues, e.g., over- and undershoot [11], mode mixing [12], end effects [13,14], unexplainable negative frequency generated when calculating instantaneous frequency using Hilbert transform [15], as well as the massive computation amount due to lack of a fast algorithm, all of which still remain on the agenda for further research. Local mean decomposition (LMD) is an alternative relatively new self-adaptive time-frequency analysis method proposed by J.S. Smith. This method can self-adaptively decompose a complex multi-component signal into a number of production functions (PFs) whose instantaneous frequencies have physical meaning. Besides, each PF component is obtained by the product of one envelope signal and one pure frequency modulated signal, of which the envelope signal is the instantaneous amplitude of this PF component. Meanwhile, the instantaneous frequency of PF component can be derived from the pure frequency modulated

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signal. Thus, by combining the instantaneous frequencies and instantaneous amplitudes of all PF components, the complete time-frequency distribution of the original signal can be obtained [15]. As compared with EMD, LMD avoids such issues as over- and undershoot resulting from the upper and lower envelope generated by adopting cubic spline interpolation in EMD, as well as negative frequency using Hilbert transform. Moreover, it is widely applied in the field of mechanical fault diagnosis thanks to its characteristics of better analysis of multi-component modulated signals [16–20]. However, LMD also suffers from issues such as end effects [21], mode mixing [22], abrupt changes in signal due to demodulation, and massive computation [23]. In particular to the issue of massive computation, LMD is more prominent as compared to EMD.

In this paper, a new self-adaptive time-frequency analysis method—local oscillatory-characteristic decomposition (LOD) is introduced [24]. This method employs mathematical operations including differential operation, coordinate domain transform and piecewise linear transform, enabling the self-adaptive and rapid decomposition of a complex signal into a series of mono-oscillatory components (MOCs). Besides, it is characterized by simple algorithm, high computation efficiency and robust real-time processing performance, which suitable for real-time analysis of mechanical fault vibration signals with non-stationary and multi-component characteristics. The LOD method based on the reference to the idea of self-adaptive time-frequency analysis for EMD and LMD. Therefore, in this paper, we firstly compare the LOD with EMD and LMD by analyzing the simulation signals, the results of which show that LOD is superior to EMD and LMD in terms of aspects such as computation time and end effects, and is more suitable for real-time online analysis. Furthermore, in terms of the characteristics of rotating machinery fault vibration signals, the LOD is applied to the analysis of gearbox and roller bearing vibration signals. The experimental signal and real signal analysis results show that the envelope analysis based on LOD method can be applied to the rotating machinery fault diagnosis effectively.

This paper is organized as follows. In Section 2, we give the main steps of the LOD method. Comparison of simulation signals analysis between LOD and other self-adaptive time-frequency analysis method is given in Section 3, which shows that superior results can be obtained by LOD. The analysis results from gearbox and roller bearing fault vibration signals are given in Section 4. Finally, we offer the conclusions in Section 5.

2. Local oscillatory-characteristic decomposition

LOD follows the basic idea of EMD and LMD, i.e., perform self-adaptive decomposition based on local oscillatory characteristics of the signal itself, thereby obtaining a series of mono-component signals whose instantaneous frequencies have physical meaning. Specific LOD algorithm comprises the following three basic operations: ① Differential operation, namely, differential operation is performed with respect to the original signal, then the initial mean function of the original signal is attained based on the differential signal. Due to the amplification of local oscillatory characteristics of signals by differential operation, thereby enabling the decomposition results to reflect more genuinely local oscillatory characteristics of the original signal; ② Coordinate domain transform operation, i.e., transform the coordinates of the original signal by predefined transform formula from the original data domain into sawtooth domain, then perform stepwise iterations in the sawtooth domain. Due to the fact that the degree of sparseness of data points at different positions of signal is changed in the sawtooth domain, thus, the decomposition error of the algorithm can be reduced; ③ Piecewise linear transform operation, i.e., perform piecewise linear transform against the original signal taking the data between adjacent extrema as one data "segment". Besides, the mean curve is also calculated by piecewise linear transform, thus, the computation efficiency and real-time processing performance of the LOD algorithm will be substantially improved.

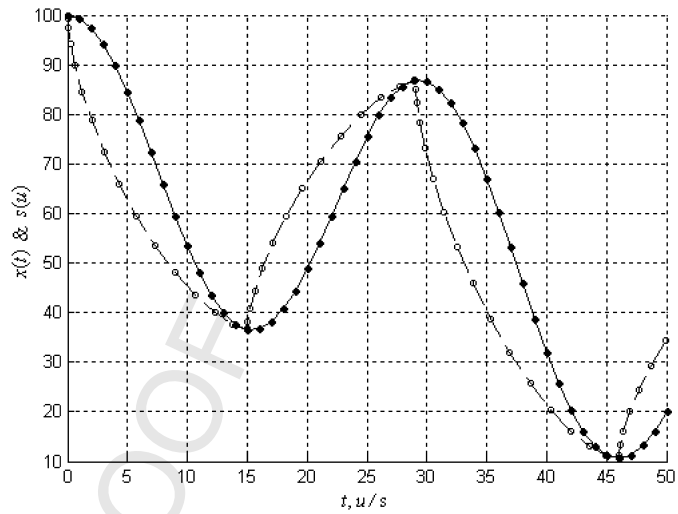

Fig. 1. Schematic diagram of signal transformation (solid line: data domain signal $x(t)$, dotted line: sawtooth domain signal $s(u)$).

LOD is adopted to self-adaptively decompose a signal into a number of components. Due to the fact that each component represents theoretically a certain oscillatory characteristic, it is therefore referred to as the mono-oscillatory component (MOC). The specific decomposition steps of LOD for any signal $x(t)$ are presented as follows:

1) Find all extrema X_k, $k = 1, 2, \cdots, M$ of signal $x(t)$ and corresponding time values τ_k, $k = 1, 2, \cdots, M$, perform linear transform against $x(t)$ between two arbitrary adjacent extrema $[X_k, X_{k+1})$, thereby obtaining a piecewise linear function $s_1(t)$. The formula of linear transform is given by:

$$s_1(t) = X_k + (X_{k+1} - X_k)\frac{t - \tau_k}{\tau_{k+1} - \tau_k} \quad k = 1, 2, \cdots, M-1 \tag{1}$$

To reduce the decomposition error of the algorithm, sawtooth transform function is defined to transform the coordinates of the original data domain (t, x) into the sawtooth domain coordinates (u, s). The transform formula is given by:

$$u(t) = \tau_k + \frac{x(t) - X_k}{X_{k+1} - X_k}(t - \tau_k) \quad t \in [\tau_k, \tau_{k+1}) \quad k = 1, 2, \cdots, M-1 \tag{2}$$

$$s(u) = x(t) \tag{3}$$

Fig. 1 presents the schematic diagram of a signal coordinates transformation, where the solid line denotes the original data domain curve with solid points as sampling points of the curve; dotted line represents the curve of sawtooth domain with hollow points as the sampling points. It can be observed that formula (2) and (3) will not change the amplitude (y-coordinate) of signal, but only compact or extend the time axis (x-coordinate). Thus, the actual effect yielded is that without changing the number of signal data points, the density of data points adjacent to signal extrema is increased whereas that of signal data points elsewhere is reduced. Therefore, without affecting the temporal and spatial operating of the algorithm, more precise information at extrema of a signal can be obtained. Hence, the decomposition precision may be improved with respect to LOD, of which the decomposition is based on the information of signal extrema.

Besides, it is worth noting that sawtooth domain transform will not modify the coordinate position and degree of sparseness of

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