Digital Signal Processing 55 (2016) 52–63

Contents lists available at ScienceDirect

Digital Signal Processing

www.elsevier.com/locate/dsp

Elimination of end effects in local mean decomposition using spectral coherence and applications for rotating machinery

Wei Guo [a,*], Lingjian Huang [a], Cheng Chen [a], Huaiwu Zou [b], Zhiwen Liu [a]

[a] School of Mechatronics Engineering, University of Electronic Science and Technology of China, Chengdu, 611731, China
[b] Shanghai Research Institute of Aerospace System Engineering, Shanghai, 20110, China

ARTICLE INFO

Article history:
Available online 22 April 2016

Keywords:
Local mean decomposition
End effects
Waveform extension
Fault diagnosis
Rotating machinery

ABSTRACT

Local mean decomposition (LMD) is widely used in signal processing and fault diagnosis of rotating machinery as an adaptive signal processing method. It is developed from the popular empirical mode decomposition (EMD). Both of them have an open problem of end effects, which influences the performance of the signal decomposition and distort the results. Using the cyclostationary property of a vibration signal generated by rotating machinery, a novel signal waveform extension method is proposed to solve this problem. The method mainly includes three steps: waveform segmentation, spectral coherence comparison, and waveform extension. Its main idea is to automatically search the inside segment having similar frequency spectrum to one end of the analyzed signal, and then use its successive segment to extend the waveform, so that the extended signal can maintain temporal continuity in time domain and spectral coherence in frequency domain. A simulated signal is used to illustrate the proposed extension method and the comparison with the popular mirror extension and neural-network-based extension methods demonstrates its better performance on waveform extension. After that, combining the proposed extension method with normal LMD, the improved LMD method is applied to three experimental vibration signals collected from different rotating machines. The results demonstrate that the proposed waveform extension method based on spectral coherence can well extend the vibration signal, accordingly, errors caused by end effects would not distort the signal as well as its decomposition results.

1. Introduction

To extract the feature signal for fault diagnosis of rotating machinery, many time frequency analysis methods have been developed, including the short time Fourier transform (STFT), the Wigner Ville distribution (WVD), the wavelet transform (WT), and so on, in which the wavelet transform method is the most commonly used, but one of its major problems is the non-adaptive basis. For analyzing a vibration signal, an adaptive signal processing method is expected to reveal the overlapping in time and frequency components and adaptively disassemble it into some simple signals, so that the feature signal of interest can be individually analyzed without the influence by other signals. The empirical mode decomposition (EMD) [1] method and the local mean decomposition (LMD) [2] are indicated by the many literatures to be good and popular adaptive methods for processing nonlinear and non-stationary signals, such as [3–5] for rotating machinery, [6] for voice signal, [7] for EEG signal, and so on. Using the EMD method, a multi-component signal is adaptively decomposed into some simpler components with amplitude and frequency modulated parameters [8]. Similarly, the LMD method decomposes it into a series of mono-components, called product functions (PFs), each of which is essentially an amplitude-modulated and frequency-modulated (AM–FM) signal [5,9,10].

Although these two methods have shown to be quite versatile in a broad range of applications, one of open problems to be solved is end effects [11–13]. During the decomposition, the signal extraction needs to identify the extrema of the analyzed signal. The interior extrema are easily identified. However, near the two end points, errors would be involved in the analyzed signal if the end point(s) is not a local maximum or minimum. Some efforts have been made to solve this problem. A sliding window fitting method [14,15] was proposed to analyze the signal within a sliding window, in which the analysis is reliable. Such technique of sliding window has been successfully applied to analyze data in Fourier analysis using various windows and continuous wavelet analyses. However, the determination of reliable windows is often analysis-method-related but not related to the analyzed signal

* Corresponding author.
E-mail address: guo.w@uestc.edu.cn (W. Guo).

http://dx.doi.org/10.1016/j.dsp.2016.04.007

itself. Accordingly, it must lead to throwing away some precious information contained in the signal near the ends [16].

Another solution to solve the problem of end effects is the extension of the analyzed signal, which is still the best basic solution. The extension based on characteristics of signal waveforms was initially proposed by Huang et al. [1]. They added characteristics waves to the treatment of end effects, in which the extra points are determined by the average of n-waves in the immediate neighborhood of the ends, and they did not mention how to determine an appropriate characteristic wave. The main idea for other extension methods is to extract the features near ends from all available samples to extend the signal, including feature-based extension (e.g. the local straight-line extension [16], self-similarity [17], Hermitian polynomials for upper and lower envelopes [18]), mirror images (e.g. axis-symmetry signal extension (ASSE) [19]), prediction methods (e.g. artificial neural network (ANN) [20], support vector regression (SVR) machine [21]), pattern comparison (e.g. an improved slope-based method [22]), and so on. Prediction methods can provide good performance on data extension, however, such computational intelligence based methods have their own shortcomings, including local minima and over-fitting in ANN and sensitiveness to parameter selection in both SVR and ANN. Lin et al. [23] proposed an approach that couples the mirror extension with the extrapolation prediction of SVR function to learn the feature of sample points near the ends, so that advantages of these two approaches can be used to guard result of the elimination of end effects in the EMD.

While methods for extending data vary, the essence of these methods is to add some extra points with minimal interior perturbations and extend the signal implicitly or explicitly beyond the existing range. These methods are based on an assumption that the extending data will repeat the form or feature of the existing data. The reliability of the estimation at a given point will sharply decrease as its distance away from the known data set increases, and thus it is necessary to be careful in expanding a signal only by adding the extrapolation data to it [23]. Otherwise, errors caused by the extension would propagate from the end to the interior of the data and even cause severe deterioration of the whole signal.

After comparing the above extension methods, the mirror image extension is easier to be put into practice, and the extension based on characteristics of signal waveforms seems to be more appropriate for the requirement to describe the complexity of problems [23]. For most of vibration signals collected by rotating machinery, the nonlinear and non-stationary properties are definite, which makes the extension based on the characteristics of the signal difficult. It is necessary to develop a method with good extension performance as well as easy operation to implement. That is the aim of this paper. Considering that the vibration signal collected from rotating machinery is a cyclostationary signal (periodic modulations of random phenomena by the rotating parts) [24,25], this paper proposes a novel spectral-feature-based waveform extension method to eliminate end effects. Using the proposed method, the part of the signal waveform that has similar frequency spectrum to one signal end can be automatically found, and then its successive waveform can be used to extend the signal. As a result, the signal keeps its cyclostationary property, and errors would not accumulate during the signal decomposition.

The rest of the paper is organized as follows. Section 2 briefly introduces the procedure of the LMD method and then illustrates its problem of end effects. Section 3 proposes a novel waveform extension method based on the spectral coherence. After that, an improved LMD method is designed. In this section, a simulated signal would be used to illustrate the proposed extension method and compare with other two popular extension methods. Section 4 uses three experimental vibration signals collected from different rotating machines to validate the effectiveness of the improved LMD method. The conclusions are drawn in Section 5.

2. Local mean decomposition and its end effects

2.1. LMD method

After using the LMD method, a multi-component signal is represented as a set of product functions (PFs), each of which is the product of an envelope signal and a purely frequency modulated signal. For a signal $x(t)$, the procedure of its decomposition process is described as follows [2,5]:

(1) Find out all the local extrema n_i and calculate the mean of two successive extrema n_i and n_{i+1}. The i-th mean value m_i is then given by

$$m_i = \frac{n_i + n_{i+1}}{2}. \tag{1}$$

All mean values m_i are connected by straight lines. The local means are then smoothed using moving averaging to form a smoothly varying continuous local mean function $m_{11}(t)$.

(2) The i-th envelope estimate a_i is given by

$$a_i = \frac{|n_i - n_{i+1}|}{2}. \tag{2}$$

The local envelope estimates are smoothed in the same way as the local means to derive the envelope function $a_{11}(t)$.

(3) Subtract the local mean function $m_{11}(t)$ from the original signal $x(t)$ and the resulting signal, $h_{11}(t)$, is given by

$$h_{11}(t) = x(t) - m_{11}(t), \tag{3}$$

and $h_{11}(t)$ is then divided by the envelope function $a_{11}(t)$, resulting in $s_{11}(t)$.

$$s_{11}(t) = \frac{h_{11}(t)}{a_{11}(t)}. \tag{4}$$

If the envelope function $a_{12}(t)$ of $s_{11}(t)$ equals to 1, the procedure stops and $s_{11}(t)$ is a purely frequency modulated signal. If not, regard $s_{11}(t)$ as the original signal and repeat the above steps until $s_{1n}(t)$ is a purely frequency modulated signal, namely, the envelope function $a_{1(n+1)}(t)$ of $s_{1n}(t)$ equals to 1. Therefore

$$\begin{cases} h_{11}(t) = x(t) - m_{11}(t), \\ h_{12}(t) = s_{11}(t) - m_{12}(t), \\ \vdots \\ h_{1n}(t) = s_{1(n-1)}(t) - m_{1n}(t), \end{cases} \tag{5}$$

where

$$\begin{cases} s_{11}(t) = h_{11}(t)/a_{11}(t), \\ s_{12}(t) = h_{12}(t)/a_{12}(t), \\ \vdots \\ s_{1n}(t) = h_{1n}(t)/a_{1n}(t). \end{cases} \tag{6}$$

(4) An envelope signal is derived by multiplying together the successive envelope estimates obtained during the iterative process described above,

$$a_1(t) = a_{11}(t)a_{12}(t)\cdots a_{1n}(t) = \prod_{q=1}^{n} a_{1q}(t). \tag{7}$$

This final envelope signal is then multiplied by the frequency modulated signal to form the first product function $\mathrm{PF}_1(t)$, which is a mono-component amplitude-modulated and frequency-modulated signal.

$$\mathrm{PF}_1(t) = a_1(t)s_{1n}(t). \tag{8}$$