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Time-varying oscillation detector based on improved LMD and robust Lempel–Ziv complexity

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ABSTRACT

A novel method based on improved local mean decomposition (LMD) for oscillation detection is proposed. Due to its capability to analyze amplitude and frequency modulated signals, LMD is especially suitable for characterizing time-varying control loop oscillations. In contrast to empirical mode decomposition (EMD), the improved LMD performs better in the following aspects: (i) ability to extract both single/multiple oscillations in process output, (ii) robustness to noise, and (iii) capability to handle non-stationary trends. In addition, improved LMD can precisely characterize the time-varying oscillations without distortion and frequency leakage even for short time series. Finally, a robust Lempel–Ziv complexity based statistic for time-varying oscillation detection is presented. Simulation examples and industrial applications are provided to demonstrate the effectiveness of the proposed LMD oscillation detector.

1. Introduction

Oscillation is one of the most common unusual phenomena encountered in process plants (Tikkala, Zakharov, & Jämsä-Jounela, 2014). Industrial surveys over the last few decades indicate that more than 60% of the loops exhibit degenerate performance and about 30% loops oscillate (Ender, 1993; Zakharov, Zattoni, Xie, Garcia, & Jämsä-Jounela, 2013). The consequences of oscillations may include inferior quality products, increased consumption of energy and raw materials, reduced average throughput and even compromised stability and safety (Guo, Xie, Ye, & Horch, 2014; Li, Wang, Huang, & Lu, 2010). Thus, before resolving the oscillation problem via proper service and troubleshooting, the automatic detection of oscillations is of crucial importance for control loop performance maintenance (Tikkala, Zakharov, & Jämsä-Jounela, 2010).

1.1. Methods for oscillation detection

With the development of research in control system performance monitoring and assessment, several methods have been presented to detect the presence of oscillations in closed-loop systems. Hägglund first developed a technique based on Integral Absolute Error (IAE) between successive zero crossings of the signal (Hägglund, 1995). Forsman and Stattin (1999) proposed a method based on the regularity of upper and lower IAEs. In the perspective of auto-covariance function (ACF) method, Miao and Seborg (1999) proposed the decay ratio approach of ACF and Thornhill, Huang, and Zhang (2003) employed the regularity of zero-crossings of the ACF for oscillation detection and period estimation.

With respect to multiple oscillations, Matsuo and Sasaoka presented a promising detection procedure based on wavelet transforms, which is essentially an adjustable window Fourier spectral analysis (Huang et al., 1998; Matsuo & Sasaoka, 2005). Its success depends on several factors including decomposition levels, choice of mother wavelet etc. Li et al. (2010) proposed a modified version of discrete cosine transform (DCT) to approximate the real-time behavior of multiple oscillations. Naghoosi and Huang (2014) applied clustering algorithm to ACF for automatic detection and frequency estimation of oscillatory variables. It is noteworthy that all above methods rely on restrictive assumptions that the oscillation should be stationary and its magnitude/frequency does not change over time (Srinivasan, Rengaswamy, & Miller, 2007), otherwise these methods are prone to make mistakes.

Empirical Mode Decomposition (EMD), firstly proposed by Huang et al. (1998), is an adaptive signal processing method of exploring local temporal characteristic. Due to its capability in dealing with nonlinear and non-stationary data, Srinivasan et al.

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(2007) and Srinivasan and Rengaswamy (2012) confirmed that EMD can handle non-stationary trends and identify the presence of dominant oscillations. However, EMD easily falls into a dilemma in which noise will increase the EMD error when taking advantage of all the extrema, while too few extrema points will inevitably give rise to distorted spline interpolation results (Cheng, Yang, & Yang, 2012). In addition, a successful EMD application also depends on careful treatments of end effect (Cheng, Yu, & Yang, 2007), model mixing (Wu, Long, Shen, Qu, & Gloersen, 2003), intrinsic mode functions (IMF) criterion (Cheng, Yu, & Yang, 2006; Cheng, Yang, et al., 2012) etc.

More recently, a new iterative decomposition method, Local Mean Decomposition (LMD), was developed by Smith (2005). LMD is particularly suitable for the processing of amplitude and frequency modulated signals (Cheng, Yang, et al., 2012; Smith, 2005; Wang et al., 2009). In contrast to EMD, smoothed local means and local magnitudes are employed in LMD to define the data envelope rather than cubic spline lines (Smith, 2005). LMD has played an indispensable role in EEG data application (Smith, 2005) and rotating machinery fault diagnosis (Cheng, Yang, et al., 2012; Wang, He, & Zi, 2009, 2010). In this study, an improved LMD method is proposed for oscillatory signal extraction from process control loop data. The main improvements of the proposed approach include (i) end effect restraining, (ii) an adaptive strategy of selecting moving average (MA) window size and enveloping the investigated loop data and (iii) improved criterion of purely frequency modulated (PFM) signal. The improved LMD method avoids the assumptions of stationary oscillation and also circumvents the extrema dilemma of EMD.

1.2. Oscillation monitoring index

After correctly extracting all of the independent components from the original signal using the improved LMD method, the challenge in choosing an appropriate statistical index for oscillation monitoring appears if time-varying oscillations are taken into consideration. As stated by Jelali and Huang (2009), there is no clear mathematical definition of oscillation and oscillations in process control are usually considered as those which exhibit a periodic pattern not completely hidden in noise (Jelali & Huang, 2009; Srinivasan & Rengaswamy, 2012). They are usually identified by analyzing one or more of the following properties of process output, (i) regularity of zero crossings, (ii) regularity of ACF and (iii) power spectrum density.

Thornhill et al. (2003) defined a widely adopted statistic based on the regularity of zero crossings of ACF. However, it is not applicable for monitoring time-varying oscillation when the frequency varies smoothly. In practice, if the pattern of a signal keeps invariant in each period, i.e. its trend and morphological characteristics are similar in different periods, the signal is also taken as an oscillation but with time-varying property. In this research, the time-varying oscillation is defined as a kind of amplitude modulated and frequency modulated (AM–FM) signal with smoothly changing amplitude and frequency (Smith, 2005; Wang et al., 2009). A typical AM–FM oscillation example is

$$s = [1 + 0.5\cos(10\pi t)]\cos[200\pi t + 2\cos(12\pi t)] \tag{1}$$

where $1 + 0.5\cos(10\pi t)$ denotes the amplitude modulated component, and $2\cos(12\pi t)$ is for frequency modulation. Note that the frequency and amplitude of s change over time, but the variation is regular. In such cases, Thronhill's index will lose effectiveness due to irregularity of zero crossings.

This paper aims at tackling this challenge by proposing an automatic time-varying oscillation monitoring index, termed as robust Lempel–Ziv Complexity (LZC) index with a *square normalization* preprocessing procedure. LZC was firstly presented by Lempel and Ziv (1976) to evaluate the complexity of finite time sequence, it has better local characterization of a signal than the regularity of ACF zero crossings. LZC has gained increasing popularity in machine health evaluation and other areas (Hong & Liang, 2009; Yan & Gao, 2004).

The rest of the paper is organized as follows. The basic LMD algorithm and Lempel–Ziv complexity are introduced in Section 2. An improved LMD method with a comprehensive comparison between LMD and EMD on signal decomposition is proposed in Section 3. In Section 4, the index design for oscillation monitoring is elaborated based on robust-LZC. Industrial case studies of the proposed approach are discussed in Section 5, which is followed by a summary in Section 6.

2. Preliminaries

In this section, a brief introduction and discussion of local mean decomposition (Smith, 2005) to analyze amplitude modulated and frequency modulated (AM–FM) signals are provided. The Lempel–Ziv complexity approach to evaluate the complexity of finite time sequence is also introduced.

2.1. Local mean decomposition

2.1.1. Brief review of LMD

LMD is an innovative decomposition method proposed by Smith (2005). LMD can decompose a complicated signal into a small set of production functions (PF), each one corresponds to the product of an envelope signal and a purely frequency modulated signal. Its decomposition process can be summarized as follows:

(I) Calculate local mean and magnitude. Determine all local extrema of the original signal $x(t)$, and then the ith local mean and magnitude value, m_i and a_i, of two successive extrema n_i and n_{i+1} are given by

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

(ii) Interpolate straight lines of local mean and local magnitude values between successive extrema. Smooth these straight lines with Moving Average (MA) filter to obtain the local mean signal $m_{11}(t)$ and magnitude envelope signal $a_{11}(t)$.

(iii) Subtracting $m_{11}(t)$ from the original data $x(t)$ yields $h_{11}(t)$

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

then demodulate its amplitude by $a_{11}(t)$,

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

If $s_{11}(t)$ is a normalized or purely frequency modulated (PFM) signal, namely, the envelope function $a_{12}(t)$ of $s_{11}(t)$ is close to 1, then go to step (iv). Otherwise, repeat the above procedures on $s_{11}(t)$ until a purely frequency modulated signal $s_{1n}(t)$ is obtained. The iteration stops when the following condition is satisfied (Cheng, Yang, et al., 2012),

$$1 - \sigma \le a_{1(n+1)}(t) \le 1 + \sigma \tag{5}$$

where $0 < \sigma < 1$ is a predefined threshold.

(iv) Multiplying the final frequency modulated signal $s_{1n}(t)$ by the envelope function $a_1(t)$ gives the first product function PF_1 of the original signal.

$$PF_1(t) = a_1(t)s_{1n}(t) = a_{11}(t)a_{12}(t)\cdots a_{1n}(t)s_{1n}(t) = \left(\prod_{q=1}^{n} a_{1q}(t)\right)s_{1n}(t) \tag{6}$$