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Improved oscillation detection via noise-assisted data analysis

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ABSTRACT

Oscillation detection is usually a precursor to more advanced performance monitoring steps such as plant wide oscillation detection and root cause detection. Therefore any false or missed detection can have serious implications. Oscillation detection is a challenging problem due to the presence of noise and multiple modes in the plant data. This paper presents an improved and robust automatic oscillation detection algorithm based on noise-assisted data analysis that can handle multiple oscillatory modes in the presence of both coloured and white noise along with non-stationary effects. The dyadic filter bank property of multivariate empirical mode decomposition has been used to accurately detect the oscillations and to calculate the associated characteristics. This work improves upon the existing auto covariance function based methods. The robustness and reliability of the proposed scheme is demonstrated via simulation and industrial case studies.

1. Introduction

Oscillation detection is an important aspect of control loop performance assessment (CLPA) owing to the fact that about 30% of all industrial control loops are reported to be oscillating (Srinivasan, Rengaswamy, & Miller, 2007). Oscillations can be caused by a variety of issues such as process degradation, poor controller tuning, presence of non-linearities, and external disturbances. Oscillations, if allowed to carry on unchecked, can adversely impact productivity, integrity and economics of any industrial process (Chaudhry, Shah, & Thornhill, 2004; Tangirala, Kanodia, & Shah, 2007).

Reliable and accurate detection of oscillation is paramount in identifying control loops requiring further investigation. Such further investigation may involve looking for the cause of oscillation within the loop itself, or looking for causes elsewhere in the plant. Thus detection of any false mode or failure to identify any real oscillation can ruin the whole diagnosis process. Furthermore, accurate estimate of the oscillation characteristics like period of oscillation and amplitude are also helpful in plant wide oscillation detection and fault localization.

Broadly speaking oscillation detection can be subdivided into two groups, namely (a) Oscillation detection in individual loops/variables, and (b) Plant wide oscillation detection where loops/variables oscillating with similar frequencies are grouped together to look for the common cause of performance degradation

The latter group is not an oscillation detection method in a stricter sense, as it only groups different variables without identifying the presence or extent of oscillations within each loop (Li, Wang, Huang, & Lu, 2010). Therefore this work will be focused on the first type, i.e. oscillation detection, and a summary of some oscillation detection methods is presented here. More detailed description can be found in review papers by Thornhill and Horch (2007) and Bacci di Capaci and Scali (2018).

Hägglund (1995) proposed an on-line and a simple yet effective procedure based on monitoring of the control error and computing integral absolute error (IAE) between successive zero crossings, to detect the oscillations. A Modified Empirical Model Decomposition (EMD) method is proposed by Srinivasan et al. (2007) where a non-constant mean from plant data is removed using modified EMD process.

Li et al. (2010) have developed a method where the Discrete Cosine Transform (DCT) is used to isolate the different frequency components in the oscillatory signal followed by checking the regularity of zero crossings in these isolated components to identify the presence or absence of oscillations. The recent list of oscillation detection methods also includes the works by Xie, Lang, Chen, Horch, and Su (2016a) and Xie, Lang, Horch, and Yang (2016b).

Several authors have investigated the use of the Auto Covariance Function (ACF) for detection and characterization of oscillations. The ACF of an oscillating signal oscillates with same period as the original signal and at the same time it is less sensitive to noise as white noise is confined to zero lag only. This idea is being used by Karra, Jelali, Karim, and Horch (2010), Miao and Seborg (1999), Naghoosi and Huang

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(2014), Srinivasan and Rengaswamy (2012), Thornhill, Huang, and Zhang (2003) and Wardana (2015) to detect the oscillations in the control loops data.

Of all the methods listed above the ACF based methods are more robust and reliable in the presence of noise, that is always present in physical measurements and can complicate the analysis to a significant extent. But in spite of all these advantages the presence of multiple oscillations in the presence of white and coloured noise needs special treatment and care even in the ACF based methods. In the work by Thornhill et al. (2003), a filter is used to filter out the different oscillatory modes before the detection procedure. Tuning of filter parameters is an uphill task and needs good understanding of the underlying process dynamics. The EMD based approach given by Srinivasan and Rengaswamy (2012) gets rid of the filter requirement and is reported to be performing better than the DCT based approach given by Li et al. (2010), and can handle non-linear and non-stationary time series, but it suffers from inherent limitations associated with the EMD process itself, i.e. the EMD process is prone to mode mixing, especially in presence of noise and multiple oscillations. Presence of coloured noise complicates the things further. This mode mixing can adversely affect the oscillation detection mechanism and has a tendency to cause erroneous results. Moreover, the accuracy of existing schemes decrease significantly with the increase in the noise variance and with the presence of coloured noise.

1.1. Contribution of this paper

In this work, the limitations of the EMD based oscillation detection process are highlighted using simulation studies as well as industrial data, and an improved oscillation detection method based on Noise-Assisted Multivariate EMD (NA-MEMD) is presented. The dyadic filter bank property of MEMD is exploited to improve the accuracy and reliability of the oscillation detection mechanism. The proposed method can handle multiple oscillations in the presence of both white and coloured noise with equal robustness and reliability. Moreover, the proposed method also helps in characterizing the oscillations caused by non-linear effects by highlighting the presence of harmonics.

This paper is organized as follows. Section 2 gives the detailed description of the proposed method with a summary of EMD and the mode mixing issues related with it. It also highlights the basics of MEMD and NA-MEMD procedure. Simulations studies are presented in Section 3 and finally industrial case studies are given in Section 4 followed by conclusions.

2. Noise-assisted oscillation detection

In this work, the use of noise-assisted multivariate EMD (NA-MEMD) is proposed to detect the presence and frequency of oscillations in the signal. This method can handle both non-linear and non-stationary time series and is found to be better than existing EMD based method proposed by Srinivasan and Rengaswamy (2012). Here the mode alignment and dyadic filter bank property of MEMD is utilized to formulate a robust and reliable oscillation detection mechanism. The advantages of the proposed method over the standard EMD based method (Srinivasan & Rengaswamy, 2012) are highlighted using Monte-Carlo simulations with varying noise levels and industrial case studies.

The input signal is decomposed into constituent IMFs using NA-MEMD. The IMFs so obtained are converted to the corresponding ACFs and the zero crossings are used to detect the presence or absence of oscillations. In this section the limitations of the standard EMD process, especially with regards to mode mixing problems, are highlighted.

Next, a brief overview of the multivariate EMD is given, followed by the steps involved in proposed oscillation detection algorithm.

2.1. Empirical mode decomposition: Basics and inherent limitations

2.1.1. Empirical mode decomposition

Empirical mode decomposition adaptively decomposes the signal into sub-components called Intrinsic Mode Functions or IMFs. Each IMF is a function that has zero mean and the number of extrema and zero crossings in the whole data set must either be equal or at most differ by one. The advantage lies in the fact that the procedure does not need any *a priori* assumption or knowledge about the underlying process dynamics (Huang et al., 1998). The EMD process basically sifts out fast oscillations from the input time series ($x(t)$) by iteratively removing slow frequencies. These slow oscillations or modes are in fact local means $m(t)$ of the envelope defined by spline fitting of the extrema.

$$d(t) = x(t) - m(t) \tag{1}$$

where $d(t)$ represents the local fast mode (Rilling, Patrick, & Paulo, 2003). The sifting process is iterated on d until it is an IMF (named $c_1(t)$). Once the IMF is extracted it is subtracted from the original signal and the sifting procedure is started again on the residue. This continues until there are no more IMFs to be extracted. If $c_i(t)$ is the ith IMF and $r(t)$ is the residue, the sifting procedure gives

$$x(t) = \sum_{i=1}^{N} c_i(t) + r(t) \tag{2}$$

where N is the total number of IMFs. The details of the procedure can be seen in Huang et al. (1998) and Rilling et al. (2003).

2.1.2. Limitations of EMD

Although the EMD process is finding its way into a number of application areas yet it is not free from problems or shortcomings. The foremost of them all, that is well known and documented, is the mode mixing problem (Gao, Ge, Sheng, & Sang, 2008). Mode mixing is defined as when one oscillatory mode (here *mode* refers to an oscillation frequency) is present in more than one IMF or one IMF contains several contrasting modes (ur Rehman, Park, Huang, & Mandic, 2013; Wu & Huang, 2009). This mode mixing can lead to erroneous results when it comes to the detection of oscillations in a signal having multiple oscillatory modes, noise and non-stationary effects. The simulation case study (Section 3) highlights the effect of this mode mixing on the oscillation detection problem.

2.2. Multivariate EMD (MEMD)

Multivariate EMD (MEMD) as the name suggests is an extension of the standard univariate EMD algorithm, to multivariate or n-dimensional signals. The term *univariate signal* here refers to a time series consisting of single variable.[1] Similarly time series having more than one variables are termed multivariate or multidimensional.[2] For instance a multivariate signal $\mathbf{X}$ consisting of n variables $x_1 \ldots x_n$ with each variable having l samples is given by

$$\mathbf{X} = \begin{Bmatrix} x_1(1) & x_2(1) & \ldots & x_n(1) \\ x_1(2) & x_2(2) & \ldots & x_n(2) \\ \vdots & \vdots & \ldots & \vdots \\ x_1(l) & x_2(l) & \ldots & x_n(l) \end{Bmatrix} \tag{3}$$

The critical issue is how to get the envelope and its local mean in a higher dimensional space. Rehman and Mandic (Rehman & Mandic, 2010) proposed to get the signal projection in multiple directions in n-dimensional space. Multiple directions are represented via direction vectors from the centre of a unit sphere to uniformly spaced points on its surface. The details can be seen in Rehman and Mandic (2010) and Aftab, Hovd, and Sivalingam (2017).

[1] The same definition applies to a *single channel* signal.

[2] Thus, a *n-dimensional* signal means a time series consisting of n variables.