Control Engineering Practice 32 (2014) 1–8

Contents lists available at ScienceDirect

Control Engineering Practice

journal homepage: www.elsevier.com/locate/conengprac

A method for detecting non-stationary oscillations in process plants

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ARTICLE INFO

Article history:
Received 6 March 2014
Accepted 17 July 2014
Available online 13 August 2014

Keywords:
Oscillation
Fault detection
Industrial application

ABSTRACT

Persistent oscillations are a common problem in process plants since they cause excessive variation in process variables and may compromise the product quality. This paper proposes a method for detecting oscillations in non-stationary time series based on the statistical properties of zero-crossings. The main development presented is a technique to remove a non-stationary trend component from a signal before applying an oscillation detection procedure. The properties and performance of the method are analyzed using simulation experiments, a comparative study using industrial benchmark data, and tests with paperboard machine data. Finally, the simulation and industrial results are analyzed and discussed.

1. Introduction

Demands to optimize and run industrial processes more efficiently are increasing constantly due to tightening global competition. Since modern industrial processes are complex and large-scale, operator-based monitoring cannot guarantee timely detection and reliable diagnosis of the faults and abnormalities. Therefore, the automatic detection and diagnosis of different abnormal and faulty conditions in the processes have become increasingly important.

A common example of such abnormal behavior of a process plant is persistent oscillations that readily propagate in the process and cause excessive variation in the process variables as well as in the product quality. They are commonly a significant reason for inefficient operation and production losses (Jämsä-Jounela et al., 2013) and therefore early detection of oscillations becomes highly important.

Oscillations have no clear mathematical definition, but are typically considered as periodic patterns in a signal that are not however disguised by noise (Karra & Karim, 2009). The oscillations in process plants are typically originated under feedback control (Desborough & Miller, 2001; Ender, 1993), and they may have various causes which have been categorized by Thornhill and Horch (2007) into non-linear and linear causes. The non-linear causes include for example extensive static friction in the control valves (see e.g. Pozo Garcia, Tikkala, Zakharov, & Jämsä-Jounela, 2013), on–off or split range control, sensor faults, process non-linearities, and hydrodynamic instabilities. The most common linear causes are poor controller tuning, controller interaction, and structural problems involving process recycles (Thornhill & Horch, 2007).

Detecting oscillations by visual inspection can be straightforward, but in case of a large-scale process plant, which may contain hundreds or thousands of signals, manual analysis becomes practically infeasible. In such cases, mathematical tools are required to determine the presence of oscillation(s) and its basic characteristics, such as period or magnitude. In Jelali and Huang (2010), a list of desired features for an oscillation detection method is presented: (i) utilization of data without further process knowledge, (ii) capability to handle slowly varying trends, (iii) robustness to white and colored noise, (iv) capability to handle multiple oscillations, and (v) completely automatic operation without human intervention.

The mathematical methods and techniques to detect oscillations are typically based on analyzing the shape or regularity of zero-crossings of a signal or its autocorrelation function, or spectral content of the signal using power spectral density or various decomposition techniques. Comprehensive reviews and comparisons of the oscillation detection methods have been presented e.g. by Horch (2006) and Choudhury, Shah, and Thornhill (2008).

The first approaches to oscillation detection were based on the regularity of large enough integral absolute error (IAE) of a control loop error signal (Hägglund, 1995; Thornhill & Hägglund, 1997). The industrial implementation of the IAE method has been discussed by Hägglund (2005). Forsman and Stattin (1999) provided a modified version of the IAE method in which the regularity of upper and lower IAEs was considered separately enabling more accurate detection of non-symmetric oscillations.

The properties of the auto-correlation function (ACF) of a signal have also been used by several authors to detect oscillatory signals. Miao and Seborg (1999) proposed a method based on the decay ratio of an ACF, whereas Thornhill, Huang, and Zhang (2003) used the zero-crossings of the ACF to determine the presence of an oscillation. The decay ratio method measures the attenuation of oscillations in the ACF of a signal to determine the presence of an oscillation. The ACF method by Thornhill et al. (2003) detects the oscillations by

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http://dx.doi.org/10.1016/j.conengprac.2014.07.008
0967-0661/

means of the regularity of zero-crossings in a filtered ACF and is capable of detecting multiple oscillations with different frequencies.

The oscillation detection methods have been developed also based on wavelets (Matsuo, Sasaoka, & Yamashita, 2003), the poles of autoregressive and moving-average models (Salsbury & Singhal, 2005). Moreover, a variety of multivariate methods have been developed to decompose spectral data using for example on principal component analysis (Thornhill, Shah, Huang, & Vishnubhotla, 2002) and non-negative matrix factorization (Tangirala, Kanoda, & Shah, 2007).

The most significant difficulty related to oscillation detection using these methods is the non-stationarity of time series. Many of the methods in the literature utilize features, such as autocorrelation, that assume the stationarity of the data. Therefore, such methods may fail if applied to time series with trends or slow variations in their mean value. Typically, linear trends are easy to remove by detrending and in some cases slowly varying, non-stationary trends could be removed using appropriate high-pass filtering. However, such procedures are very challenging to automate in order to analyze large amounts of signals without manual effort. For example filtering techniques usually require parameters to be determined specifically in each case.

Non-stationarity may not be a severe issue when analyzing control loops in which the setpoint remains constant for a long time and the controller is able to maintain the controlled variable in the proximity of the setpoint. However, in cases where the oscillation detection is focused on the manipulated variable, cascade controllers, or on control loops which act as servo-type controllers following a varying setpoint, addressing the non-stationary trends becomes more important. In addition, oscillations may be found also in measurements that are not a part of a control loop (Thornhill & Horch, 2007).

In order to address the aforementioned issues, the aim of this paper is to propose a method to detect oscillatory disturbances which is capable to handle non-stationary signals and can be used automatically without manual preprocessing. The method utilizes a baseline computation procedure to stationarize the signals, computes the median and mean absolute deviation of the intervals between consecutive zero-crossings, and incorporates them into a robust statistic index. As a result, the oscillation detection also becomes robust against noise in the analyzed signals. Thus, the method becomes attractive for analyzing measurements signals and control loops of process plants.

The paper is organized as follows. Section 2 provides a detailed description of the proposed oscillation detection method. Next, the simulation experiments and the tests on industrial data are described in Section 3. The results and analysis for the simulation and industrial tests are presented in Sections 4 and 5, respectively. Finally, the results are discussed and the paper is concluded in Section 6.

2. The robust zero-crossing method for oscillation detection in non-stationary time series

The proposed method, referred hereinafter as the robust zero-crossing (RZC) method, utilizes the statistical properties of intervals between consecutive zero-crossings (ZC) to detect oscillations. Due to a developed baseline computation procedure the RZC method is capable to detect oscillations also in non-stationary signals.

The RZC method first computes the moving trend, or the "baseline" of a non-stationary signal by finding the consecutive ZC intervals and the local minimum and maximum values of the signal between them. For a discrete-time signal $x(t),\ t=1,\dots,n$, the time instants of zero-crossings $t_{z,i}$ are defined as

$$t_{z,i}=\{t|\text{sign}\{x(t-1)-b(t-1)\}\neq\text{sign}\{x(t)-b(t)\}\},\quad i=1,\dots,m \tag{1}$$

where $b(t)$ is the baseline of the signal at time t and m is the number of zero-crossings in $x(t)$. The local maxima and minima, a_i^+ and a_i^-, are used to calculate the shift in the signal's baseline for each interval:

$$b(t)=\begin{cases}a_i^-+\dfrac{a_i^+-a_i^-}{2}, & t=t_{z,i},\quad i=3,4,\dots,m\\ b(t-1) & \text{otherwise,}\end{cases} \tag{2}$$

where

$$a_i^+=\max\{x(t_1)-b(t_1),\ x(t_2)-b(t_2)\},\quad t_{z,i-1}\le t_1\le t_{z,i},\quad t_{z,i-2}\le t_2\le t_{z,i-1}, \tag{3}$$

and

$$a_i^-=\min\{x(t_1)-b(t_1),\ x(t_2)-b(t_2)\},\quad t_{z,i-1}\le t_1\le t_{z,i},\quad t_{z,i-2}\le t_2\le t_{z,i-1}, \tag{4}$$

The above formulation ensures that a_i^+ and a_i^- represent correctly the oscillation's maximum and minimum amplitudes whether the last half period has been positive or negative. In order to handle outliers in the signal, a_i^+ and a_i^- are compared to their mean values $\overline{a}^+=1/(i-1)\sum_{j=1}^{i-1}a_j^+$ and $\overline{a}^-=1/(i-1)\sum_{j=1}^{i-1}a_j^-$, respectively. If the current maximum a_i^+ violates the condition

$$a_i^+>\overline{a}^++3\sigma_{a^+}, \tag{5}$$

where σ_{a^+} is the standard deviation of $a_j^+,\ j=1,\dots,i-1$ the previous value of a_i^+ is used: $a_i^+=a_{i-1}^+$. The minima are treated similarly, the equivalent condition being $a_i^-<\overline{a}^--3\sigma_{a^-}$.

Before $x(t)$ can be stationarized, the baseline is corrected by backward shifting and interpolation. The backward shifting is done because $b(t)$ is computed based on the last two half periods and therefore it lags behind the true baseline, the estimate of which is denoted as $b_c(t)$ hereinafter. The backward shifting is defined as $b_c(t_{z,i})=b(t_{z,i+1})$, and the interpolation as follows:

$$b_c(t)=b_c(t_{z,i})+(t-t_{z,i})\frac{b_c(t_{z,i})-b_c(t_{z,i-1})}{t_{z,i}-t_{z,i-1}},\quad t_{z,i-1}<t\le t_{z,i} \tag{6}$$

Finally, the signal is stationarized by subtracting the computed baseline $x_s(t)=x(t)-b_c(t)$. If the signal is already stationary, this procedure does not alter its shape or properties.

Next, the determination of the presence of an oscillation is based on calculating the regularity of zero-crossings. In an oscillating signal, in which the period is close to regular, the average interval between the ZCs differs from that of a non-oscillating or noise signal and the variation of the intervals is small compared to their average length.

The above can be incorporated into a statistical test that is used to detect oscillations. The test is based on the fact that the distribution of time interval between consecutive zero-crossings $\Delta t_{z,i}=t_{z,i}-t_{z,i-1}$ in non-oscillating signals resembles typically the geometric distribution. This can be shown rigorously for a pure Gaussian noise signal and it can be reasonably assumed for other non-oscillating signals. To demonstrate this, Fig. 1 shows examples of such signals with the corresponding zero-crossing distributions, which appear to have a shape similar to the geometric distribution.

Since the mean and standard deviation of geometric distribution are equal, the following hypotheses can established:

$$H_0:\overline{\Delta t_z}=\sigma_{\Delta t_z},\quad H_1:\overline{\Delta t_z}=3\sigma_{\Delta t_z}, \tag{7}$$

where $\overline{\Delta t_z}$ is the mean and $\sigma_{\Delta t_z}$ is the standard deviation of the interval between consecutive zero-crossings, respectively.

In order to test the hypothesis, a statistic r can be calculated as follows (Thornhill et al., 2003):

$$r=\frac{1}{3}\frac{\overline{\Delta t_z}}{\sigma_{\Delta t_z}} \tag{8}$$

If the value of r is greater than one, the presence of an oscillation can be determined.