Aalto University

Aaltodoc

OPEN ACCESS

This is an electronic reprint of the original article.
This reprint may differ from the original in pagination and typographic detail.

Author(s):   Tikkala, Vesa-Matti & Zakharov, Alexey & Jämsä-Jounela, Sirkka-Liisa

Title: A method for detecting non-stationary oscillations in process plants

Please cite the original version:

A method for detecting non-stationary oscillations in process plants

Vesa-Matti Tikkala [*] **Alexey Zakharov** [*]
Sirkka-Liisa Jämsä-Jounela [*]

[*] *Aalto University School of Chemical Technology,*
Department of Biotechnology and Chemical Technology,
P.O. Box 16100, 00076 Aalto, Finland
(email: vesa-matti.tikkala@aalto.fi)

Abstract: 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 non-stationary trend component from the analysed signals before applying an oscillation detection procedure. First, the method extracts the signal's baseline that is utilized to stationarize the signal. Then, an index describing the regularity of the stationarized signal's zero-crossings is computed in order to determine the presence of oscillation. The properties and performance of the method are analysed in simulation studies. Furthermore, the method is comprehensively tested with industrial data in a comparative study in which the proposed method is tested against other oscillation detection methods using industrial benchmark data and in tests on paperboard machine process . Finally, the simulation and industrial results are analysed and discussed.

Keywords: Fault detection, oscillation, diagnosis, industrial application

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 behaviour of a process plant are 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 and Karim, 2009). The oscillations in process plants are typically originated under feedback control (Desborough and 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, 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 and 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 are presented: (i) utilization of data without further process knowledge, (ii) capability to handle slowly varying trends, (iii) robustness to white and coloured 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 analysing 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 et al. (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 and 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 were 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 et al. (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 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 et al., 2003), the poles of autoregressive and moving-average models (Salsbury and Singhal, 2005). Moreover, a variety of multivariate methods have been developed to decompose spectral data using for example on principal component analysis (Thornhill et al., 2002) and non-negative matrix factorization (Tangirala et al., 2007).

The most significant difficulty related to oscillation detection using these methods is the non-stationarity of the 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 analyse large amounts of signals without manual effort. For example filtering techniques usually require parameters to be determined specifically in each case.

Therefore, to address the aforementioned issues, the aim of this paper is to propose a method that is capable to handle non-stationary signals and can be used automatically without manual pre-processing to detect oscillatory disturbances. 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 analysed signals. Thus, the method also becomes attractive for analysing 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 experiments are presented in Section 3. The results of the simulation tests and industrial data 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 $x(t)$, $t = 1, \ldots, n$, the time instants of zero-crossings $t_{z,i}$ are defined as

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

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:

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

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.

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 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:

$$b_c(t) = \begin{cases} b_c(t_{z,i}) + (t - t_{z,i}) \dfrac{b_c(t_{z,i}) - b_c(t_{z,i-1})}{t_{z,i} - t_{z,i-1}}, & t_{z,i-1} < t < t_{z,i} \\ b_c(t), & t = t_{z,i} \end{cases} \tag{5}$$

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 an 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 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, Figure 1 shows examples of
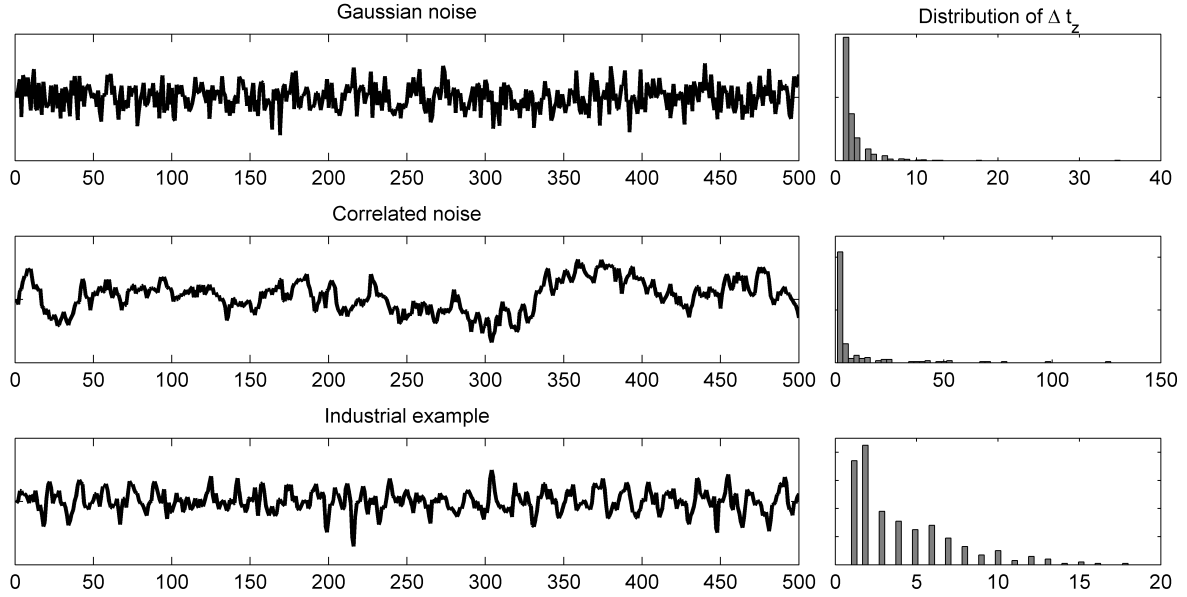
Fig. 1. Examples of non-oscillating signals and their zero-crossing distributions: Gaussian noise (top row), correlated noise (middle row) and industrial measurement signal (bottom row).

such signals with the corresponding zero-crossing distributions, which appear have a shape similar to the geometric distribution.

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

$$H_0 : \bar{\Delta t}_z = \sigma_{\Delta t_z} \quad H_1 : \bar{\Delta t}_z = 3\sigma_{\Delta t_z}, \qquad (6)$$

where $\bar{\Delta t}_z$ 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):

$$r = \frac{1}{3}\frac{\bar{\Delta t}_z}{\sigma_{\bar{\Delta t}_z}} \qquad (7)$$

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

The above index uses the mean and standard deviation of the ZC interval which may cause problems due to measurement noise, when the method is implemented in time domain . In contrast to the ACF method by Thornhill et al. (2003), the current method has no inherent filtering properties and therefore needs to address the noise by other means. To this end, robust statistics are utilized: the mean is replaced with the median $\tilde{\Delta t}_z = \mathrm{median}(\Delta_{z,i})$ and the standard deviation is replaced with the mean absolute deviation (MAD) from median defined as:

$$\mathrm{MAD}(\Delta t_z) = \frac{1}{m-1}\sum_{i=1}^{m}(|t_{z,i} - \tilde{\Delta t}_z|). \qquad (8)$$

Median is a more robust measure of central tendency in case of asymmetrically tailed distributions or outliers. These features are also often present in distributions related to zero-crossings. Furthermore, median absolute deviation was selected due to its ability to address outliers in the data better than regular standard deviation, which consequently increases the robustness of the detection

result. Consequently, the index r_{RZC} can be re-written as

$$r_{RZC} = \frac{1}{3}\frac{\tilde{\Delta t}_z}{\mathrm{MAD}(\Delta t_z)} \qquad (9)$$

Finally, the presence of an oscillation is determined if $r_{RZC} > 1$ with an estimated period $p_{RZC} = 2\tilde{\Delta t}_z$. The RZC algorithm can be summarized as follows:

(1) Compute the baseline $b(t)$ the signal $x(t)$.
  (a) Determine the initial baseline value $b(1) = x(1)$ and the sign of the first half period.
  (b) Find the next zero-crossing and compute the corresponding values of a_i^+ and a_i^-.
  (c) Compute the new baseline level $b(t_{z,i}) = a_i^- + \frac{a_i^+ + a_i^-}{2}$.
  (d) Repeat steps 1b and 1c until all m zero-crossings have been processed.
(2) Compute the corrected baseline by backward shifting $b_c(t_{z,i}) = b(t_{z,i+1})$ and interpolating according to (5).
(3) Compute the stationarized signal $x_s(t) = x(t) - b_c(t)$.
(4) Find the zero-crossings $t_{z,i}$ of $x_s(t)$ and compute $\Delta t_z(i)$.
(5) Compute the median and median absolute deviation of Δt_z and calculate the r_{RZC}-statistic.

3. EXPERIMENT DESCRIPTION

The RZC method was tested and analysed in simulation tests and in a comparison study using industrial benchmark data. The simulation tests aimed at studying the effect of noise to the performance of the method, whereas the objective of the industrial tests was to investigate the method's operation using real measurement signals and to compare its performance against other similar oscillation detection techniques.
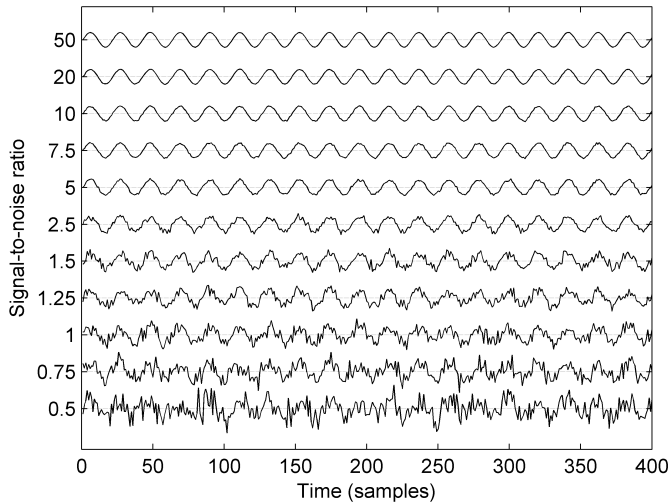
Fig. 2. Test signals for signal-to-noise ratio analysis

Fig. 3. Industrial test data from a paperboard machine process

3.1 Simulation tests

In the simulation tests, the performance of the method was analysed using signals with sinusoidal oscillations and superimposed random noise. Noise is always present in industrial data and it may have a significant effect on the performance of the method. To study its effect on the results, a set of oscillating signals with different signal-to-noise ratios ranging from 0.5 to 50 were generated. The signal-to-noise ratio was defined as a ratio of variances of the oscillation and a normal random signal: $SNR = \frac{\sigma_{\mathrm{osc}}}{\sigma_{\mathrm{noise}}}$.

A set of eleven test signals, with a sine wave that has a period of 20 samples, was generated. Randomly generated noise sequences were added to the test signals and the resulting signals are presented in Figure 2.

3.2 Comparison study on industrial benchmark data

A study using a benchmark data set provided by Jelali and Huang (2010) was carried out in order to test the RZC method and to compare its performance against other oscillation detection methods. The methods used in the comparison test are the IAE method by Hägglund (1995), modified IAE method by Forsman and Stattin (1999) and the ACF method by Thornhill et al. (2003). These methods are also based on calculating regularity properties related to zero-crossings in the analysed signals. In addition, they are simple to implement in an industrial setting, do not require complex preprocessing, and have been widely tested using industrial data.

The other methods were implemented according to the descriptions in the respective publications and the limit values for the oscillation indices were selected based on the given suggestions. For the IAE method, an oscillation is detected if $r_{IAE} > 1.3$. The limit for the mIAE method was $r_{mIAE} > 0.3$, whereas the ACF method uses a limit of $r_{ACF} > 1$. The tuning parameters related to the mIAE method, $\alpha = 0.55$ and $\gamma = 0.75$, were determined according to the suggestions given by Forsman and Stattin (1999).

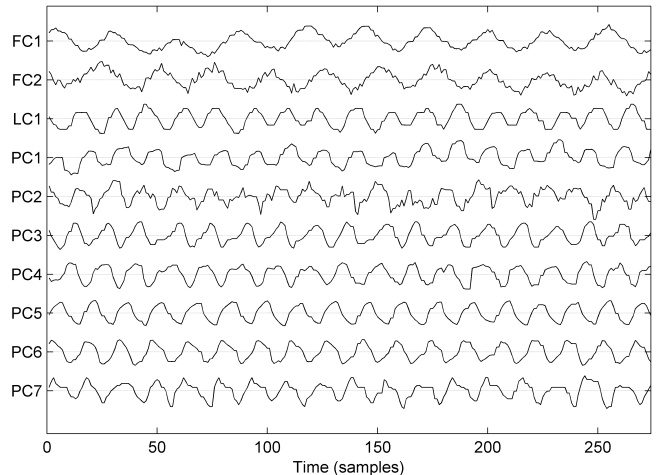A set of 35 signals was selected from the benchmark data set for the comparison study analysis. The main criteria for the signal selection were to include a wide range of signals with different properties: stationary/non-stationary, clean/noisy. Signals were excluded if they did not contain a sufficient number of oscillation periods, contained abrupt step-wise changes. In addition, the most of the pure noise signals were neglected, since they do not add any value to the investigation. The signals used in the study are listed in the results section, Table 1.

3.3 Industrial tests on board machine data

Another test on industrial data was conducted using a data set from an paperboard machine process, later referred to as the board machine. Data from ten control loops were collected. The loops included two flow control loops from the stock preparation section as well as one level control loop and seven pressure control loops from the drying section. These control loops are among the most important ones in the board machine, since they are involved in the control of the product quality. The flow control loops in stock preparation are critical due to their role in controlling the flow ratios of the board raw materials. Whereas, the drying section loops are directly used to control the moisture of the board, which is one of the most important quality variables.

Time series of 270-1000 samples were collected with a sampling interval of ten seconds. A part of the data is presented in Figure 3 which shows that oscillatory behaviour is clear in each loop. However, in some signals the oscillation shape is slightly irregular and especially the flow loops FC1 and FC2 as well as PC2 are quite noisy.

4. SIMULATION RESULTS

The simulation results illustrate the operation of the method, as presented in Figure 4. It shows a non-stationary signal with a varying trend and a superimposed regular oscillation with a period of 20 samples. The top panel shows the signal and the computed baseline which follows closely the non-stationary trend of the signal. In the bottom plot, a more detailed presentation of the method is shown. The detected baseline $b(t)$ indicates the

Fig. 5. The effect of noise on the RZC method performance. Detected period (top panel) and oscillation index r_{RZC} (bottom panel) as a function of signal-to-noise ratio.

result of the first step of the method where the baseline levels are calculated according to the minima a_i^- and maxima a_i^+ of the zero-crossing intervals. The line depicted with squares indicates the corrected baseline $b_c(t)$ after the backward shifting and interpolation step. It represents the second step of the method and illustrates how the non-stationary trend is extracted from the original signal.

In order to investigate the effect of noise on the performance, the method was also evaluated using a set of oscillatory signals having various signal-to-noise ratios, see Figure 2. The results indicate that the RZC method is capable to detect oscillations correctly in signals with relatively low SNR. Figure 5 shows the estimated oscillation period and the computed oscillation statistic r_{RZC} as a function of SNR. Also, the detection limit $r_{lim} = 1$ is shown.

It is noted that the oscillation is detected correctly with SNRs greater or equal to 1.25, at which the oscillation index is $r_{RZC} = 1.12$. However, the estimated period is lower ($p_{RZC} = 14$) than the true period. The period is estimated correctly for SNRs higher than 1.5. In order to demonstrate the benefits of using the robust statistics in the oscillation index, the standard oscillation indices calculated according to (7) are also presented. It can be seen that especially in the lower SNR range the robust r_{RZC} performs better than the standard index. For example, at SNR of 1.25 the standard index fails to detect the oscillation and underestimates the period even more than the robust index: $r = 0.89$ and $p = 12.28$.

These results indicate that the performance of the current method is at acceptable level in case of noisy signals. However, in extreme cases, where the noise variance is of similar magnitude compared to the signal variance, the results are affected and the oscillation is not detected properly. It is notable that in very noisy signals the estimated oscillation period appears to be smaller than the true one. The results still suggest that the method's performance is sufficient for industrial applications.

5. INDUSTRIAL RESULTS

5.1 Comparison test results

The RZC method was tested using the benchmark data signals along with three other methods and their performance was analysed and compared. For the sake of brevity, only three cases are presented and discussed here in detail in order to provide an insight to the properties of the RZC method.

The first case example deals with a non-stationary signal CHEM7, time series of which is presented in the top left panel of Figure 6. The signal has a clear increasing trend and the magnitude of the oscillation is slightly varying. During the time between 1000-1500 samples, the magnitude of the oscillation becomes almost zero and makes the recognition of these periods impossible. However, in this case, the RZC method provides a correct detection result with $r_{RZC} = 3.03$ and a correctly estimated period $p_{RZC} = 22$ samples, while the true period appears to be around 22–24 samples. Also, the IAE and mIAE methods provide correct detections with respective index values $r_{IAE} = 1.87$ and $r_{mIAE} = 0.54$. Both methods estimated also the oscillation period correctly. However, the ACF method failed to detect the oscillation due the non-stationary trend.

By studying the distribution of zero-crossing intervals in the right hand side panel of Figure 6, it can be clearly seen that the majority of them are between 8-12 samples. However, there are some intervals between 20-30 samples which are caused by the variations in the oscillation magnitude around $t = 1000 - 1500$ samples. Fortunately, due to the robustness of the oscillation index computation, these do not affect the detection result.

Next case (Figure 7) exhibits a noisy signal which clearly has a periodic pattern with a non-sinusoidal shape. The period of the oscillation is approximately 16-20 samples. In this case, the RZC method fails to detect the oscillation because of the noise in the signal $r_{RZC} = 0.58$. In particular, there are significant noisy parts close to the centre line of the oscillation which causes spurious zero-crossing detections. The noise appears to be the cause for the IAE and mIAE methods to also fail in this case. The only method that succeeds to detect the oscillation is the ACF method, $r_{ACF} = 1.94$ and $p_{ACF} = 16.75$ samples, which is due the filtering property of the autocorrelation function.

The third example case is a noise signal that has no oscillation, see Figure 8. The RZC method provides a correct detection result, $r_{RZC} = 0.84$. The IAE and mIAE methods do not detect any oscillations, whereas the ACF method detects falsely an oscillation with a period of 15.35 samples while $r_{ACF} = 2.29$. The false detection is due to a dominant frequency in the signal that caused fluctuations to the auto-correlation function. Examination of the distribution plot of the zero-crossings in Figure 8 shows a shape close to the geometric distribution which is characteristic to pure noise signals.

The full results of the comparison study are presented in Table 1, which lists the tested signals with the period of oscillation as well as the corresponding detection results
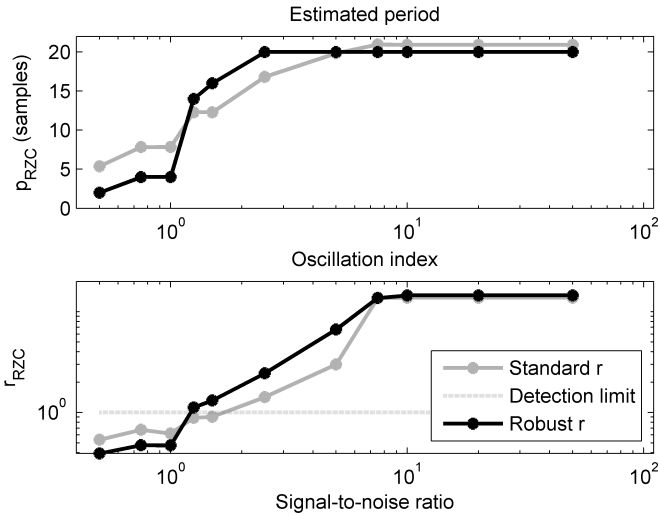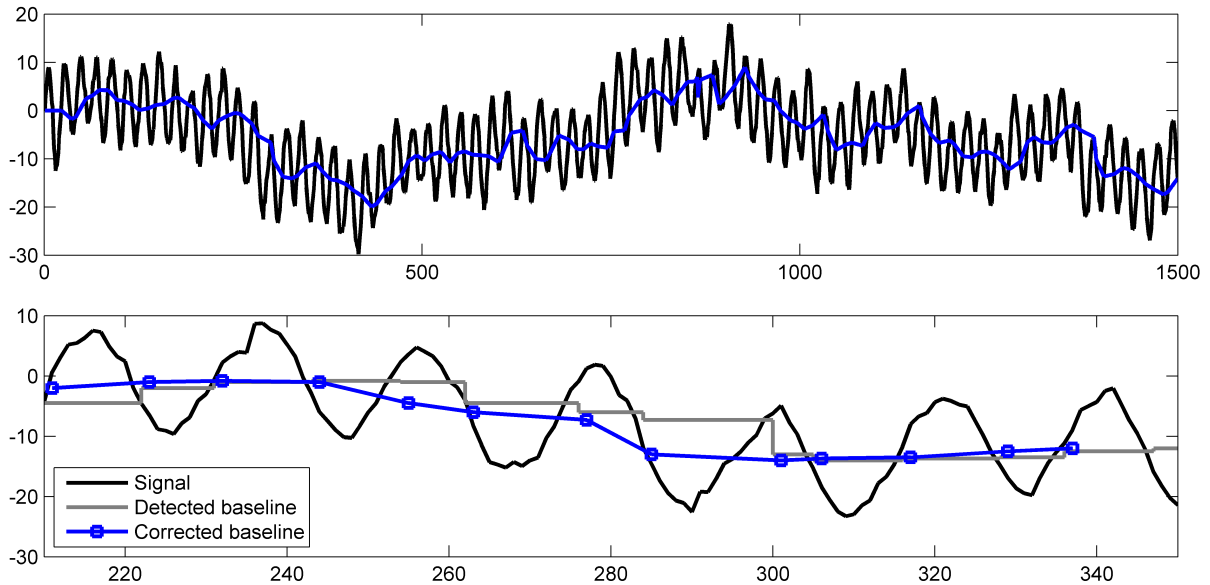
Fig. 4. Oscillation detection using the proposed RZC method. Top panel shows a non-stationary oscillating signal and the computed baseline. Bottom panel shows a detailed illustration of the detected baseline and the final corrected baseline.

Fig. 6. Case example 1: CHEM7, detected oscillation, $r_{RZC,7} = 3.03$. Original signal (top left), stationarized signal (bottom left), the distribution of zero-crossing intervals (top right), and the autocorrelation (bottom right).

and the estimated periods by each method. The periods shown in the second column have been estimated through a careful visual inspection. For each method, the calculated oscillation indices and binary indices indicating the detection decisions are reported. The table entries with bold numbers show the correct detection results.

Finally, a summary of the comparison study is presented in Table 2, which reports the percentages of correct results, false alarms, missed alarms for each method. The results show that the RZC method has the highest rate of correct results, 85.7%, the smallest number of missed alarms, and no false alarms at all. These results are encouraging in perspective of industrial implementation for automatic anal-

ysis of measurement signals. The rate of correct detection results is sufficiently high for the method to be reliable, also with unpreprocessed industrial data. In addition, the fact that no false alarms were occurred is a very positive result and contributes significantly to the overall reliability in industrial use.

Table 2. Summary of the oscillation detection results using the benchmark data.

	RZC	IAE	mIAE	ACF
Correct results	85.7	37.1	51.4	68.6
False alarms	0	0	2.9	11.4
Missed alarms	14.3	62.9	45.7	20.0
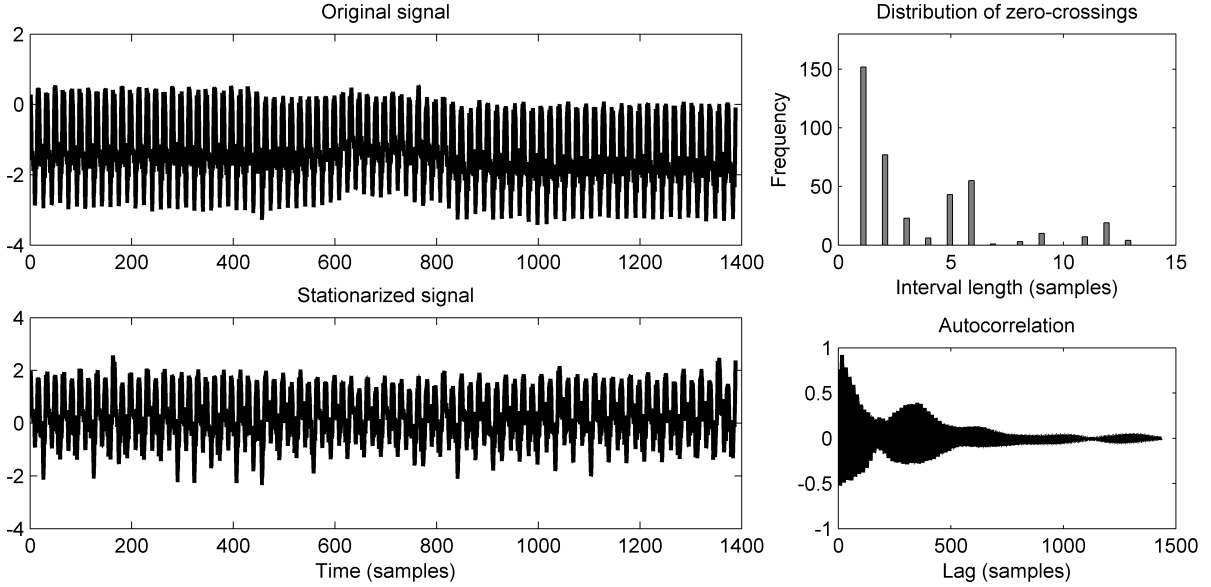
Fig. 7. Case example 2: CHEM24, missed detection, $r_{RZC,23} = 0.58$. Original signal (top left), stationarized signal (bottom left), the distribution of zero-crossing intervals (top right), and the autocorrelation (bottom right).
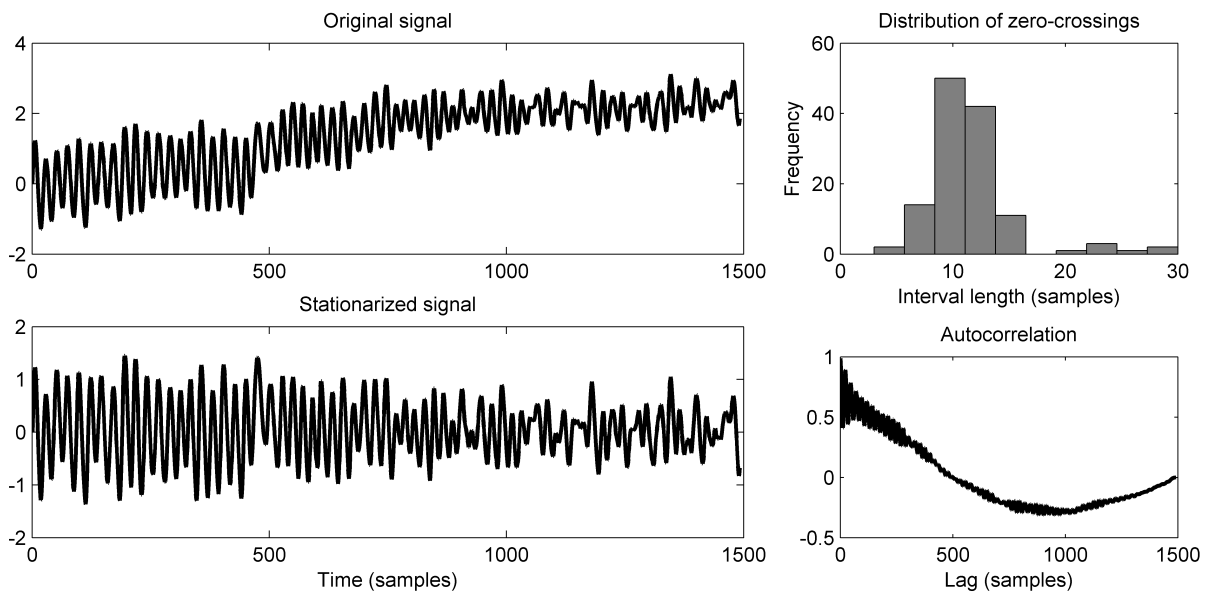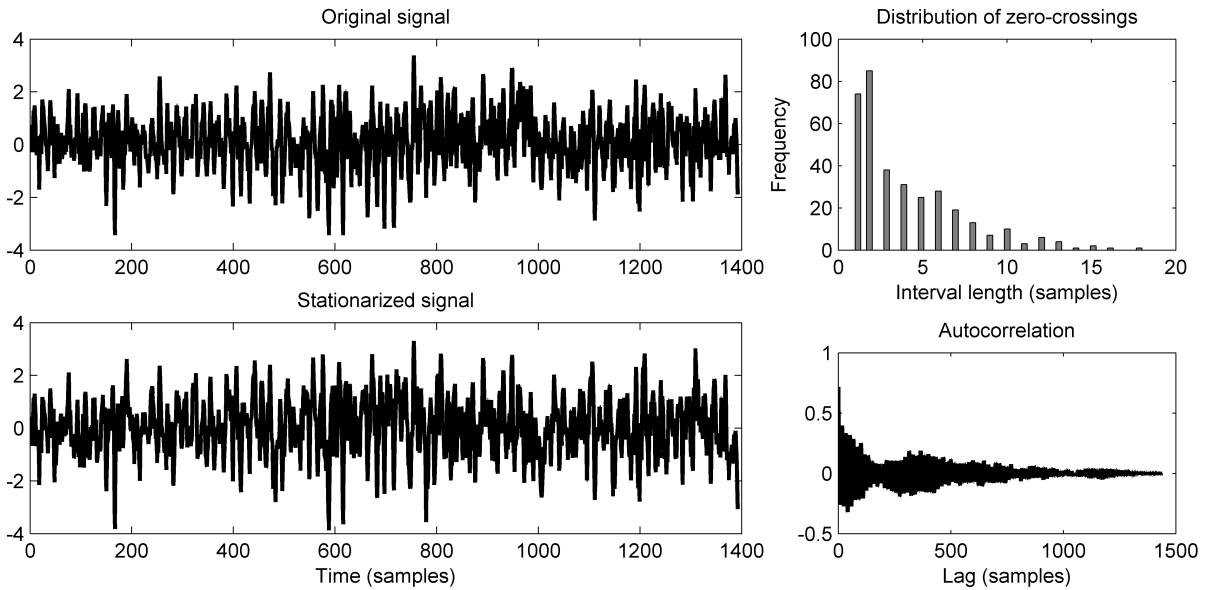

Fig. 8. Case example 23: CHEM23, no oscillation, $r_{RZC,24} = 0.84$. Original signal (top left), stationarized signal (bottom left), the distribution of zero-crossing intervals (top right), and the autocorrelation (bottom right).

5.2 Test results on board machine data

The RZC method was tested using a data set from an industrial board machine process. The data contained oscillations with different and sometimes irregular shapes and some of the signals were quite noisy. However, the test results were encouraging: in each case the oscillation was detected successfully and the estimated periods were close to the true periods of the oscillations.

Table 3 summarizes the computed oscillation indices r_{RZC} and the estimated periods p_{RZC}. The oscillations in the flow control loops were clearly detected, the oscillation index having a value of 1.31 in both cases as well as the

periods were correctly estimated. The reported results for the level control loop are equally good.

In case of the pressure control loops, there are some variation in the results. The oscillation and its period is correctly detected in loops PC1, PC3, PC4, PC5 and PC6. However, in loop PC2, the noise in the signal makes the oscillation slightly more difficult to detect; the oscillation index is barely over the detection limit. In addition, the noise causes the period to be estimated smaller than it actually is. According to visual inspection the period is approximately 12–15 samples (2–2.5 minutes), whereas the RZC method reports a period of 10 samples. Similar problem occurs with loop PC7 in which the estimated

Table 1. Results of the comparison test of different oscillation detection methods using industrial benchmark data. Bolded table entries indicate correct detection results.

Signal	Period	RZC			IAE			mIAE			ACF		
		p_{RZC}	r_{RZC}	i_{RZC}	p_{IAE}	r_{IAE}	i_{IAE}	p_{mIAE}	r_{mIAE}	i_{mIAE}	p_{ACF}	r_{ACF}	i_{ACF}
CHEM1	140–170	**151**	**1.90**	**1**	148.80	0.73	0	128.60	0.14	0	**161.89**	**2.75**	**1**
CHEM2	190–230	**142**	**1.11**	**1**	145.00	0.39	0	94.50	0.00	0	**205.33**	**1.83**	**1**
CHEM3	–*	–	**0.77**	**0**	–	**0.13**	**0**	–	**0.28**	**0**	–	NaN	**0**
CHEM4	139–143	**140**	**16.85**	**1**	–	0.39	0	–	0.16	0	**136.71**	**3.51**	**1**
CHEM5	120–130	–	0.05	0	–	0.46	0	–	0.15	0	**125.71**	**63.21**	**1**
CHEM6	22–25	**22**	**4.37**	**1**	–	0.43	0	–	0.17	0	**23.81**	**4.70**	**1**
CHEM7	22–24	**22**	**3.03**	**1**	**23.20**	**1.87**	**1**	**22.20**	**0.54**	**1**	–	0.58	0
CHEM8	8–10	–	0.28	0	–	0.47	0	–	0.06	0	204.33	3.02	1[a]
CHEM9	120–130	**126**	**6.51**	**1**	**126.87**	**3.31**	**1**	**116.83**	**0.83**	**1**	**125.13**	**4.68**	**1**
CHEM10	15–18	**16**	**2.96**	**1**	**16.84**	**2.45**	**1**	–	0.26	0	**16.18**	**5.27**	**1**
CHEM11	125–135	–	0.08	0	–	0.46	0	–	0.04	0	**132.38**	**11.89**	**1**
CHEM12	–	–	**0.19**	**0**	–	**0.44**	**0**	–	**0.04**	**0**	129.56	2.10	1
CHEM13	17–24	**20**	**1.93**	**1**	–	0.41	0	–	0.11	0	–	0.35	0
CHEM14	35–45	**36**	**1.12**	**1**	–	0.09	0	104.82	0.38	1[b]	–	0.32	0
CHEM15	7–10	**8**	**4.42**	**1**	**7.19**	**1.53**	**1**	–	0.15	0	**7.46**	**1.03**	**1**
CHEM16	85–95	**89**	**3.66**	**1**	–	0.34	0	–	0.30	0	**90.70**	**18.37**	**1**
CHEM17	17–20	**18**	**1.69**	**1**	–	0.26	0	–	0.22	0	–	0.16	0
CHEM18	16–18	**16**	**3.00**	**1**	–	0.98	0	**17.34**	**0.38**	**1**	**16.93**	**5.51**	**1**
CHEM19	15–19	**18**	**1.89**	**1**	–	0.31	0	**22.25**	**0.30**	**1**	–	0.19	0
CHEM20	40–80	–	0.30	0	–	0.43	0	–	0.04	0	**49.00**	**3.77**	**1**
CHEM21	–	–	**0.68**	**0**	–	**0.72**	**0**	–	**0.08**	**0**	–	0.97	**0**
CHEM22	–	–	**0.78**	**0**	–	**0.78**	**0**	–	**0.09**	**0**	30.11	1.58	1
CHEM23	–	–	**0.84**	**0**	–	**0.98**	**0**	–	**0.07**	**0**	15.36	2.29	1
CHEM24	16–20	–	0.58	0	–	0.52	0	–	0.23	0	**16.75**	**1.94**	**1**
CHEM25	16–18	**16**	**2.81**	**1**	–	0.95	0	**17.13**	**0.40**	**1**	**16.88**	**6.18**	**1**
CHEM26	–	–	**0.21**	**0**	–	**0.57**	**0**	–	**0.07**	**0**	55.78	2.65	1
PP1	120–170	**134**	**1.55**	**1**	–	0.33	0	–	0.18	0	**152.36**	**4.32**	**1**
PP2	–	–	**0.32**	**0**	–	**0.38**	**0**	–	**0.06**	**0**	–	0.19	**0**
PP3	130–145	**135**	**3.35**	**1**	–	0.50	0	**133.77**	**0.35**	**1**	**133.15**	**19.01**	**1**
PP4	55–60	**56**	**4.65**	**1**	–	0.28	0	–	0.13	0	**57.12**	**34.59**	**1**
POW1	18–22	**20**	**4.24**	**1**	–	0.30	0	**20.22**	**0.37**	**1**	**19.66**	**4.50**	**1**
POW2	56–58	**58**	**4.81**	**1**	**58.82**	**1.88**	**1**	**58.42**	**0.49**	**1**	**58.79**	**25.09**	**1**
POW3	–	–	**0.30**	**0**	–	**0.44**	**0**	–	**0.09**	**0**	81.59	1.13	1
POW4	42–50	**44**	**1.98**	**1**	–	0.60	0	**46.32**	**0.46**	**1**	**48.23**	**7.26**	**1**
POW5	40–50	**40**	**1.25**	**1**	–	0.48	0	**37.30**	**0.34**	**1**	**49.41**	**6.47**	**1**

* missing period length indicates no oscillation
[a] ACF method detects an oscillation, but not the correct one
[b] mIAE method detects an oscillation, but gives wrong period

period is 14 samples, while the true period being 15–18 samples. In this case, the error is however smaller.

Despite the aforementioned faults the results can be considered very positive. They give another clear indication that the RZC is capable of detecting oscillations in industrial data due to its stationarization procedure and robust oscillation statistic.

Table 3. Oscillation detection results on the board machine data.

Loop	Period		p_{RZC}	r_{RZC}
	samples	minutes		
FC1	27–30	4.5–5.0	26	1.31
FC2	20–23	3.3–3.8	20	1.31
LC1	16–17	2.7–2.8	16	3.54
PC1	13–17	2.2–2.8	16	2.75
PC2	12–15	2.0–2.5	10	1.06
PC3	15–18	2.5–3.0	16	3.98
PC4	15–19	2.5–3.2	16	3.15
PC5	14–17	2.3–2.8	16	6.93
PC6	17–18	2.8–3.0	16	8.37
PC7	15–18	2.5–3.0	14	2.66

6. CONCLUSIONS

This paper presented a method for detecting oscillations in non-stationary signals. The proposed method detected the zero-crossings of the signal in order to compute its baseline. The signal was stationarized and the regularity of the zero-crossing intervals was studied using robust statistics in order to determine the presence of an oscillation.

The method was tested with simulation and industrial data. In the simulation tests, it was studied how measurement noise affects the performance of the method. As a result, it was concluded that the proposed oscillation index contributes significantly to the robustness of the method and therefore the RZC method would be usable in practical applications. The industrial tests revealed that, in terms of performance, the method is comparable to other proven methods found in the literature. In addition, it is successfully capable of detecting oscillations in industrial measurements and control loops.

The RZC method possesses several attractive features which make it suitable for industrial implementation in large-scale processes. First, the method is capable of analysing large amount of signals automatically, since

there are no tuning parameters and no data preprocessing required. Secondly, the method is robust against noise and the rate of false alarms was negligible in the presented industrial tests.

In future research, the main objectives are to further develop the method by improving the handling of abrupt variations in the signals and to test the method more comprehensively with larger amounts industrial data.

REFERENCES

Choudhury, M.A.A.S., Shah, S.L., and Thornhill, N.F. (2008). *Diagnosis of Process Nonlinearities and Valve Stiction.* Springer, 1st edition.

Desborough, L. and Miller, R. (2001). Increasing customer value of industrial contol performance monitoring — Honeywell's experience. In *Proceedings of CPC VI*, 172–192. Tucson (AZ), USA, Jan 7–12, 2001.

Ender, D. (1993). Process control performance: not as good as you think. *Control Engineering*, 40(10), 180–190.

Forsman, K. and Stattin, A. (1999). A new criterion for detecting oscillations in control loops. In *European Control Conferenre ECC'99*, 878. Karlsruhe, Germany, August 31 - September 3, 1999.

Hägglund, T. (1995). A control loop performance monitor. *Control Engineering Practice*, 3(11), 1543–1551.

Hägglund, T. (2005). Industrial implementation of on-line performance monitoring tools. *Control Engineering Practice*, 13, 1383–1390.

Horch, A. (2006). Benchmarking control loops with oscillations and stiction. In *Process Control Performance Assessment – From Theory to Implementation*, 227–257. Springer-Verlag, New York.

Jämsä-Jounela, S.L., Tikkala, V.M., Zakharov, A., Pozo Garcia, O., Laavi, H., Myller, T., Kulomaa, T., and Hämäläinen, V. (2013). Outline of a fault diagnosis system for a large-scale board machine. *International Journal of Advanced Manufacturing Technology*, 65(9), 1741–1755.

Jelali, M. and Huang, B. (2010). *Detection and diagnosis of stiction in control loops — state of the art and advanced method.* Springer-Verlag, London, 2nd edition.

Karra, S. and Karim, N. (2009). Comprehensive methodology for detection and diagnosis of oscillatory control loops. *Control Engineering Practice*, 17, 939–956.

Matsuo, T., Sasaoka, H., and Yamashita, Y. (2003). Detection and diagnosis of oscillations in process plants. In *Proceedings of the 7th International Conference on Knowledge-based Intelligent Information and Engineering Systems (KES2003)*, 1258–1264. Oxford, UK, September 3–5, 2003.

Miao, T. and Seborg, D.E. (1999). Automatic detection of excessively oscillatory feedback control loops. In *Proceedings of the 1999 IEEE International Conference on Control Applications*, 359–364. Kohala Coast — Island of Hawai'i, Hawai'i, USA, August 22–27, 1999.

Salsbury, I. and Singhal, A. (2005). A new approach for ARMA pole estimation using higher-order crossings. In *2005 American Control Conference*, 4458–4463. Portland (OR), USA, June 8–10, 2005.

Tangirala, A., Kanoda, J., and Shah, S.L. (2007). Non-negative matrix factorization for detection and diagnosis of plantwide oscillations. *Industrial and Engineering Chemistry Research*, 46, 801–817.

Thornhill, N.F. and Hägglund, T. (1997). Detection and diagnosis of oscillations in control loops. *Control Engineering Practice*, 5(10), 1343–1354.

Thornhill, N.F. and Horch, A. (2007). Advances and new directions in plant-wide disturbance detection and diagnosis. *Control Engineering Practice*, 15, 1196–1206.

Thornhill, N.F., Huang, B., and Zhang, H. (2003). Detection of multiple oscillations in control loops. *Journal of Process Control*, 13, 91–100.

Thornhill, N.F., Shah, S.L., Huang, B., and Vishnubhotla, A. (2002). Spectral principal component analysis of dynamic process data. *Control Engineering Practice*, 10.