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Real-time Detector for Time-variant Oscillation with Modified Intrinsic Time-scale Decomposition ⋆

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Abstract: An online detector for time-variant oscillation in a univariate time-series is proposed. This paper is motivated by the fact that it is still an open issue to implement the real-time oscillation detector which is applicable to non-linear, non-stationary and intermittent oscillations. The proposed procedure is based on Intrinsic Time-scale Decomposition (ITD) and contains an improved iteration termination condition of ITD. A novel hypothesis test with an improved statistic of variation coefficient enables the online monitoring of the time-variant oscillations. Simulation examples and industrial applications are provided to demonstrate the effectiveness of the online detector.

Keywords: Monitoring and performance assessment; Process control applications; Advanced control technology

1. INTRODUCTION

An oscillatory process variable is one of the most common abnormal phenomena in process industries. The consequence of oscillations may include fluctuations of product quality, increased consumption of energy and raw materials, and compromised stability and safety (Wang et al. [2013]). Automatic detection of oscillation can help the operators to focus their attention on control loops that might have performance problems and has become a standard activity in control performance assessment (Srinivasan et al. [2007]).

Existing oscillation detection techniques for a single time series can be divided into off-line and on-line techniques. Most of the existing methods are off-line, including Integral Absolute Error (IAE) method (Hägglund [2005]), the auto-covariance function (ACF) method (Thornhill et al. [2003]) and spectral envelope method (Jiang et al. [2007]). More recent methods provide off-line solutions for detecting oscillating time series with non-stationary trend and non-linearity, including wavelet transform (WT), discrete cosine transform (DCT) and the empirical mode decomposition (EMD) (Matsuo et al. [2003];Wang et al. [2013];Srinivasan et al. [2007]).

On the other hand, a prompt indication of the oscillation presence in real time is crucial for the instant compensation of the negative effects of oscillations. Although most of the off-line techniques can be implemented on-line with the help of a moving supervision window, an improper window size may delay the detection of oscillation and it has not been adequately addressed on the sample-by-sample inspecting of every single period of oscillation (Thornhill and Horch [2007]). Hägglund [2005] firstly designed a real-time window-free oscillation detector which utilizes the IAE between two consecutive instances of zero crossings of a time series. This approach, however, cannot distinguish the oscillation frequencies. Salsbury and Singhal proposed an auto-regressive and moving-average (ARMA) model method with identification of undamped poles for online oscillation detection (Salsbury and Singhal [2005]). It is only applicable to time series containing single oscillations.

To deal with the multi-oscillating signal, wavelet (Matsuo et al. [2003]) and DCT (Wang et al. [2013]) are commonly adopted as pre-specified dictionary matrices for sparse representation of the signal. Wang et al. [2013] proposed a modified version of DCT to realize the online DCT with an adaptive supervision time window to approximate the real-time behavior of oscillations. However, it is contradictory to depict the instantaneous information and the slowly oscillating component at the same time with a determined supervision window length. In addition, wavelet and DCT do not preserve the nonlinear features of the process variable which may be helpful to determine the oscillation are caused by valve stiction or other reasons. The online implementation of EMD is based on a finite size of moving window of the inspected variable. Too short supervision window size will result in distorted IMFs, which renders the interpretation of the oscillation mode a difficult task.

A desirable online oscillation detector should have the following features: (i) Applicability to intermittent, non-linear and mean-nonstationary oscillations, (ii) Rapid and efficient computations, (iii) Responsive and online implementation with statistic monitoring and analysis. To meet these above requirements, this paper introduces a real-time

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oscillation detector based on an improved Intrinsic time-scale decomposition (ITD). ITD is specifically formulated for non-linear and non-stationary signals. It can decompose a complex signal into several Proper Rotation Components (PRCs) and a residual (Frei and Osorio [2007]). For the sake of online oscillation detection, this article improves the original ITD by introducing a rapid backward redecomposition procedure as well as a revised oscillation hypothesis test on the zero-crossings of PRCs.

The rest of the article is organized as follows. The original ITD is introduced in Section 2. The oscillation detector is proposed in Section 3. A numerical example and industrial cases are discussed in Section 4 and 5. A conclusion is made in Section 6.

2. INTRINSIC TIME-SCALE DECOMPOSITION

Given a time series X_t, define the baseline-extracting operator $\mathcal{L}$ and proper-rotation-extracting operator $\mathcal{H}$, which extracts X_t into a baseline signal L_t in a manner that causes the residual H_t to be a proper rotation. More specifically, X_t can be decomposed as

$$X_t = \mathcal{L}X_t + (1-\mathcal{L})X_t \triangleq \mathcal{L}X_t + \mathcal{H}X_t = L_t + H_t \quad (1)$$

let $\{\tau_k, k = 1, 2, ...\}$ denote the local extrema positions of X_t, and $\tau_0 = 0$. Suppose that L_t has been defined on τ_k and X_t is available for $[\tau_k, \tau_{k+2}]$. For simplicity, let X_k and L_k denote $X_t(\tau_k)$ and $L_t(\tau_k)$, respectively. A piecewise linear baseline and proper rotation of X_t on interval $[\tau_k, \tau_{k+2}]$ can be decomposed as follows:

$$\mathcal{L}X_t = L_t = L_k + \left(\frac{L_{k+1} - L_k}{X_{k+1} - X_k}\right)(X_t - X_k), \quad (2)$$

$$\mathcal{H}X_t = H_t = (1-\mathcal{L})X_t = X_t - L_t, \ t \in (\tau_k, \tau_{k+1}] \quad (3)$$

$$L_{k+1} = \lambda\left[X_k + \left(\frac{\tau_{k+1} - \tau_k}{\tau_{k+2} - \tau_k}\right)(X_{k+2} - X_k)\right] + (1-\lambda) X_{k+1} \quad (4)$$

λ is typically selected around 0.5. The baseline L_t is constructed as a linearly transformed contraction of X_t in order to make the residual function H_t monotonic between $\{\tau_k\}$, a necessity for H_t to be proper rotations. It is a single-wave analysis in combination with morphological features of the signal, which allows a rapid and efficient implementation of the decomposition in real-time.

Once the input signal is decomposed into L_t and H_t, the process can be repeated by using the baseline signal L_t as an input. The iteration continues until a monotonic baseline signal – the 'trend' is obtained. The iterations decompose the raw signal into a sequence of proper rotations. The overall procedure can be expressed as

$$\begin{aligned} X_t &= \mathcal{H}X_t + \mathcal{L}X_t = \mathcal{H}X_t + (\mathcal{H}+\mathcal{L})\,\mathcal{L}X_t \\ &= \left(\mathcal{H}(1+\mathcal{L}) + \mathcal{L}^2\right)X_t = \left(\mathcal{H}\sum_{k=0}^{p-1}\mathcal{L}^k + \mathcal{L}^p\right)X_t, \end{aligned} \quad (5)$$

where $\mathcal{H}\mathcal{L}^k X_t$ is a proper rotation extracted at $k+1^{th}$ iteration, and $\mathcal{L}^p X_t$ is the monotonic baseline signal representing the trend of X_t, also known as the residual of intrinsic time-scale decomposition.

3. PROPOSED ONLINE OSCILLATION DETECTOR

The main idea of the proposed oscillation detector is to isolate the oscillation modes of a time series via modified ITD procedure for online implementation, and to detect the oscillatory behaviors with a hypothesis test on coefficient of variation (CV) of each PRC.

3.1 Modified ITD for online implementation

Online oscillation detector requires a rapid and efficient algorithm to deal with real-time measurement data. ITD provides a solution with single-wave analysis which can be performed online.

A slow but regular oscillation component requires more samples to be discovered, while oscillations with shorter periods should be detected much earlier which have been oscillating for periods in the same samples length. In oscillation detection methods with moving supervision window, e.g. EMD and DCT, longer window is required to discover the slow-oscillating component, which sacrificed the speed in detecting the short-period or intermittent behavior of oscillations. In real-time implementation of an oscillation detector, it is desired to individually capture each oscillation mode of process variable as soon as possible.

Recall the iteration procedure as $\mathcal{L}^{k+1}X_t = (\mathcal{H}+\mathcal{L})\,\mathcal{L}^k X_t$, whose termination condition is that $\mathcal{L}^p X_t$ to be monotonic. A time series containing multiple oscillation or random walking trend may distort the monotonic baseline $\mathcal{L}^p X_t$ with instantly coming real-time measurements, consequently inducing unexpected local extrema in $\mathcal{L}^p X_t$ which violates termination condition. A further decomposition results in extraction of more low-frequency PRCs which is usually unnecessary for oscillation detection.

To this end, the original ITD is improved for real-time oscillation detection in two folds: (i) the modified iteration procedure and termination condition, specifically for oscillation detection purpose is proposed to improve the quality of PRCs and non-stationary trend description, (ii) the PRC extraction procedure via ITD is updated into a new version - ITD with online backward redecomposition - to meet the requirements of real-time application.

Modified Procedure of ITD The first modification to ITD relates to its termination condition. Original ITD procedure requires a monotonic residual to ensure that all proper rotations with all corresponding local extrema have been extracted in PRCs. It is unnecessary for oscillation detection purpose since some random walking trend with few extrema is not relative to oscillation mode. An oscillation index criterion is adopted to substitute the original termination condition on monotonicity. Only if the residual is considered to contain a potential oscillating behavior should be further decomposed. The oscillation index should be robust to the most frequent types of uncertainties in the signal, especially to those time-variant oscillation patterns.

A peak-based approach is recommended to define the half-periods and oscillation peaks (Zakharov et al. [2013]). Given a residual signal $r(k) = \mathcal{L}^p X_t(k)$ and a possible integer upper-bound for the half-period length d. The symbol m_i^+ will be used for the location of the maximum in the i-period, while m_i^- will be used for the location of the minimum in the same period. The search for the values m_i^+ and m_i^-, with i = 1,2,..., is made according to the following formulas:

$$m_1^+ = \arg \max_{k=1,..,2d} r(k), \tag{6}$$

$$m_i^\pm = m_i^\pm + \arg \max_{k=d/2,..,d} r(m_i^\mp + k) \tag{7}$$

Similarity of two subsequent periods Tm_i^+ and Tm_i^- is evaluated using the correlation coefficient $C(i)$, where $Tm_i^\pm = m_i^\pm - m_{i-1}^\pm$. Re-sample Tm_i^+ and Tm_i^- to ensure they are in the same length.

$$I_{osc}(d) = \max\{\theta : \theta \leqslant C(i) \text{ for 80\% of i}\} \tag{8}$$

$$I_{osc} = \max_d I_{osc}(d) \tag{9}$$

If the index is below 0.70, it is typically impossible to recognize any oscillations in the residual and it can be confirmed that the signal is non-oscillating. Hence, the termination condition of ITD is modified as the oscillation index I_{osc} of the residual $r(k)$ is under 0.70.

The other modification to ITD is on the iteration procedure. Using the notation H_t^λ to denote the dependence of H_t in the equation on the parameter λ, an identity is derived as $H_t^\lambda = (0.5/\lambda)\, H_t^{0.5}$. It is proved that λ simply determines the amplitude of the PRC extracted at each iteration, which means the frequency distribution of an PRC remains unchanged with the variety of λ. Therefore, larger λ will decrease the number of PRC. In industrial applications, λ should be adjusted according to the noise level. The default parameter λ is 0.5, which is applicable to the most common types of industrial data. It is recommended to choose $\lambda = 0.45$ for low noise level, and $\lambda = 0.55$ for high noise level.

Backward Reconstruction Intrinsic Time-scale Decomposition is naturally available for online signal analysis. For a finite length of time series, iteration of ITD is ceased by the termination condition, resulting in a finite number of PRCs. However, the decomposition level is unidentified with constantly up-coming data. In order to determine the decomposition depth of ITD and achieve the promptness of the oscillation detector, a so-called backward redecomposition (BR) procedure is developed. It ensures the efficient computation in isolating different frequency components – especially the slow-oscillating component. Short-period oscillations are prior to be inspected than the long-period ones, without the constraints of supervision window length. This is a significant advantage over the Hilbert transform based approaches, which require longer windows of data and are not suited for single waves or short oscillations. BR utilizes the following propositions of ITD (Frei and Osorio [2007]),

Proposition 1. H_t is a proper rotation on the interval $[\tau_1, \tau_N]$ for any $N \geqslant 1$. For a PRC $\mathcal{L}^k X_t$ at the kth level of ITD, it shares the same local extrema with $\mathcal{HL}^k X_t$ when the decomposition iteration applied to $\mathcal{L}^k X_t$.

Proposition 2. $\mathcal{HL}^{i+1} X_t$ on $[\tau_k, \tau_{k+1}]$ is obtained through a linear transformation, with only necessity that $\mathcal{L}^i X_t$ on $[\tau_k, \tau_{k+2}]$ and $\mathcal{L}^{i+1} X_t(\tau_k)$ are available.

An illustration of the online ITD method is basically presented in Frei and Osorio [2007]. Proposition 1 shows the ability of ITD to preserve the extrema locations of original time-series in the decomposed PRCs. Those local

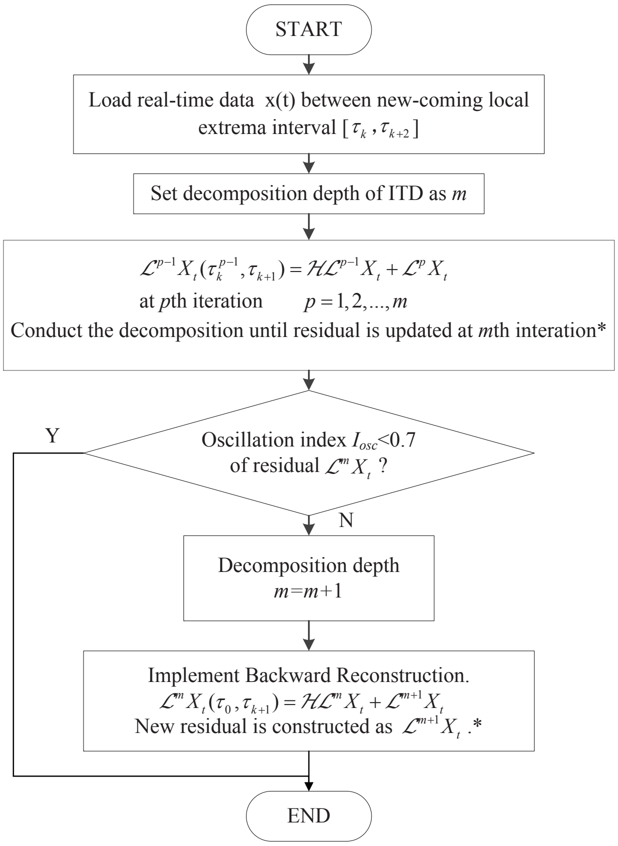

Fig. 1. Flowchart of Backward Redecomposition procedure

extrema represent relational oscillating behaviors. Proposition 2 indicate the irrelevance of history data (before τ_k) in defining baseline and rotation signal on $[\tau_k, \tau_{k+1}]$. Therefore, a proper rotation can be computed between times of successive extrema as soon as the segment has been obtained. In other words, a PRC extracted at pth iteration – $\mathcal{HL}^{p-1} X_t$ on $[0, \tau_k^p]$ always remains unchanged once it is constructed no matter what up-coming data after τ_k^p behaves, where τ_k^p denotes the last local extrema (except endpoint) of the pth PRC .

BR procedure is implemented to identify the decomposition level of online ITD. Decomposition depth of ITD is increased when the current residual component at mth level $\mathcal{L}^m X_t$ does not satisfy the modified termination condition. A further decomposition on the previous history data on the current residual of ITD – $\mathcal{L}^m X_t$ on the interval $[0, \tau_k^p]$, which is in reverse direction (backward) to the up-coming real-time data. A flowchart is presented in Figure 1 for illustration of the backward redecomposition procedure. τ_k^{p+1} denotes the position of the last local extrema (except for the endpoint) in $\mathcal{L}^{p+1} X_t$. τ_0 denotes the begin time of implementing the oscillation detector, usually $\tau_0 = 0$. The new-coming extrema from original real-time data $x(t)$ are identified as τ_k.

3.2 *Testing Statistic Design for real-time monitoring*

In practice, an oscillation is considered to be regular if the standard deviation σ_T of the zero-crossing period $T(i)$ is less than one third of its mean value μ_T (Thornhill et al.

[2003]). A hypothesis test is proposed based on coefficient variable η, defined as $\eta = \mu_T/\sigma_T$, which measures the variability relative to the mean. A time series is concluded to be oscillatory if its coefficient variable satisfies

$$\eta > 3. \tag{10}$$

It has been used as a fundamental step in the oscillation detection method. However, the basic test needs some improvement in real-time applications. Estimation of $\hat{\eta}$ highly depends on the number of zero-crossings, because $\eta > 3$ depicts the asymptotic behavior of mass data.

The first improvement on the hypothesis test is increasing robustness of the detector to noisy PRCs. Noise segment may induce spurious zero-crossings which significantly decrease $\hat{\eta}$. As a result, some oscillation patterns may fail to be detected. A clustering procedure should be implemented before zero-crossings are reported to hypothesis test. It is noted that only the minor waves in PRCs with small amplitudes and periods should be removed. The significant behaviors in PRC may indicate a time-variant feature of an oscillation. To this end, a clustering procedure is developed in combination of periods $T(i)$ and amplitude $A(i)$ for single waves of PRC. Some waves $(T(k), A(k))$ should be concluded as spurious ones in a PRC and excluded from zero-crossing maps if the following inequalities holds,

$$T(k) < \mu_T - \sigma_T, A(k) < \mu_A - \sigma_A. \tag{11}$$

μ and σ are the mean and standard deviation of the corresponding sequence.

The second improvement is taking short-time oscillation behavior into consideration. Thornhill recommended at least ten samples of $T(i)$ for the hypothesis test, because fewer than four samples would yield unreliable estimates of μ_T and σ_T. It extended the warming up time for the detector to determine an oscillation. Since intermittent behavior is successfully extracted via ITD and preserved in PRCs, it is desirable to revise the hypothesis test to be incorporate the number of periods into consideration. The revised hypothesis test is based on the coefficient variable estimation (Gulhar et al. [2012]), with (1-α)100% confidence interval is $\frac{\sqrt{N-1}}{\sqrt{\chi^2_{N-1,1-\alpha/2}}}\frac{\hat{\mu}_T}{\hat{\sigma}_T} < \eta < \frac{\sqrt{N-1}}{\sqrt{\chi^2_{N-1,\alpha/2}}}\frac{\hat{\mu}_T}{\hat{\sigma}_T}$, where N is the number of zero-crossing periods $T(i)$, $\hat{\mu}_T$ and $\hat{\sigma}_T$ are estimated mean and standard deviation from zero-crossing periods $T(1), T(2), .., T(N)$ in a finite length. Therefore, the revised hypothesis test based on the $\hat{\eta}$ is defined as its lower bound is less than 3. An oscillation is detected if the following inequality holds,

$$\hat{\eta} = \frac{\sqrt{N-1}}{\sqrt{\chi^2_{N-1,1-\alpha/2}}}\frac{\hat{\mu}_T}{\hat{\sigma}_T} > 3 \tag{12}$$

In order to achieve the promptness and robustness of detecting intermittent oscillation behaviors, it is recommended to choose no more than ten zero-crossings. It is noted that parameter N does not affect the ITD procedure, as a result, a prior indication for short-period oscillation is still available. A flowchart is presented in Figure 2 for illustration of calculating the statistic $\hat{\eta}$ for a single PRC.

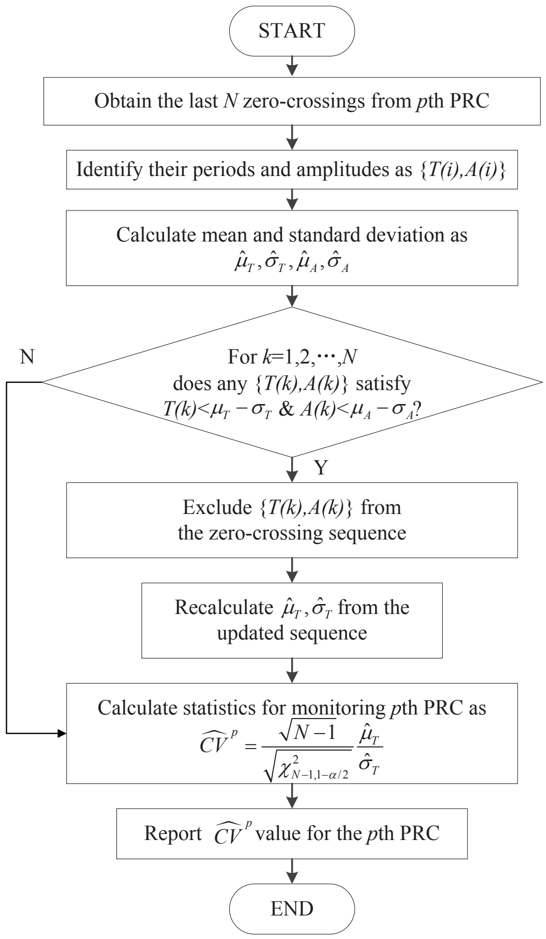

Fig. 2. Flowchart of statistic $\hat{\eta}$ calculation for PRC

3.3 Implementation of the online oscillation detector

The underlying idea of the oscillation-detection procedure is to conclude that an oscillation is present if the $\hat{\eta}$ of an extracted PRC exceeds the limit, which in result satisfied $\hat{\eta} > 3$. Given the real-time measurement of a time series $x(n)$ as shown at the top of Figure.3, the online oscillation detector is implemented in the following steps:

Step 1. Load real-time measurement data $x(n)$ until a new local extrema point of $x(n)$ is identified at $n = \tau_k$.

Step 2. Extract PRCs of $x(n)$ via modified ITD with BR procedure. Let PRC at pth level be $x^p(n)$.

Step 3. Apply the real-time oscillation monitor to the updating PRCs. Calculate real-time statistic $\hat{\eta}^p$ for the $x^p(n)$.

Step 4. If $\hat{\eta}$s of one or more PRCs are detected to exceed the limit as $\hat{\eta}^{p_i}(n_k) > 3$, it is concluded that an oscillation mode is detected in $x^{p_i}(n)$ at $n = n_k$.

Step 5. Go back to Step 1 and repeat.

4. NUMERICAL SIMULATION

In this section, a numerical simulation example is presented to illustrate the proposed oscillation detector. This example focuses on the most common time-variant feature

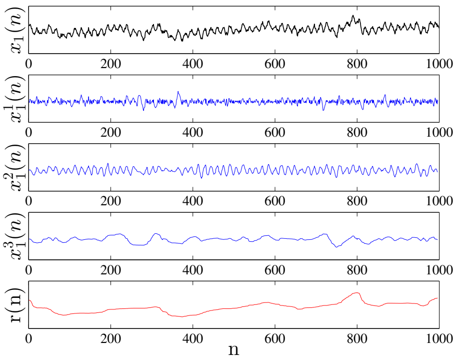

Fig. 3. Example. Mean-nonstationary data with its PRCs

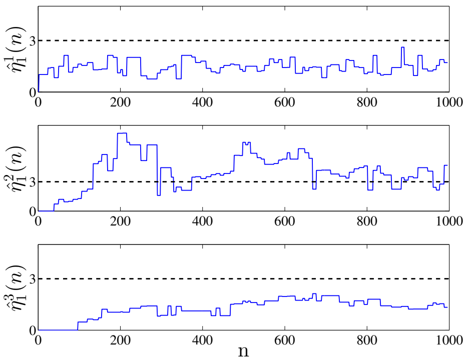

Fig. 4. Oscillation monitoring charts on Example

of oscillations in industrial control loops – non-stationary trend. It explains the necessity of modified procedure of ITD in real-time applications. A time series $x_1(n)$ with an oscillation $A(n)$ and a non-constant mean $w(n)$ is generated, as shown in Figure 3.

$$x_1(n) = w(n) + A(n),$$
$$w(n) = v(n)/(1 - 0.98z^{-1}), A(n) = 2.0\sin(0.4n).$$

$v(n)$ is a white noise sequence with $\sigma_v^2 = 1.0$. $w(n)$ is the response of a loop with a closed-loop pole on the stability boundary, excited by $v(n)$. $A(n)$ is an external disturbance. The monitoring procedure is presented in Figure 4. A PRC is concluded to be oscillatory, since its $\hat{\eta}$ significantly exceeded the limit at n=300. Noise and trend are also extracted via the modified ITD, whose $\hat{\eta}$s denied the possibility of oscillation existence. α is 0.5 as default. The revised termination condition successfully stopped the iteration at residual $x_1^4(n)$. It is not possible to find oscillations in $x_1^4(n)$ due to its oscillation index, even though the residual is not monotonic.

5. CASE STUDIES

Industrial examples are presented to illustrate the online application of the proposed oscillation detector.

Case 1. This case presents a multi-oscillating process variable $y_1(n)$ from a control loop. It illustrates the importance of backward redecomposition mechanism in the promptness of the real-time detector. $y_1(n)$ contains a slow but principal oscillation. There is also a weak oscillation from

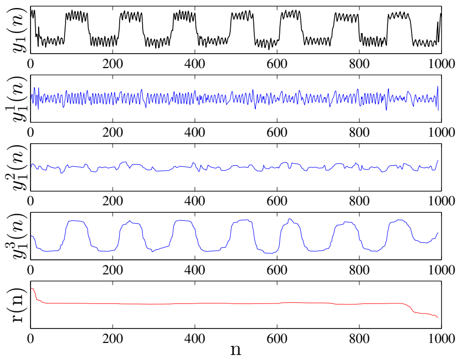

Fig. 5. Case 1. Control loop with multiple oscillation

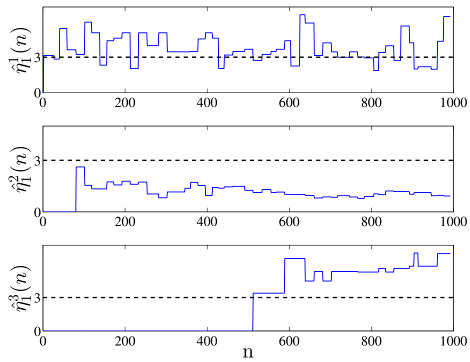

Fig. 6. Oscillation monitoring charts on Case 1

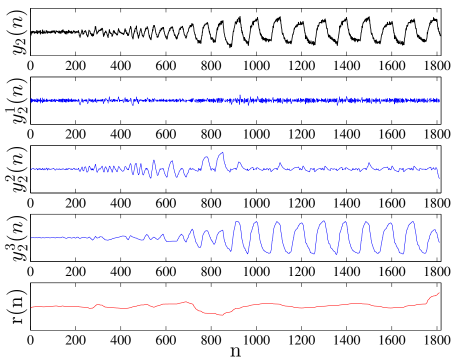

Fig. 7. Case 2. Control loop with decreasing performance

a possible external disturbance. The time trend of $y_1(n)$ is shown on top of Figure 5. With modified ITD, short-period oscillations can be extracted and identified much earlier than long-period ones. A real-time monitoring of $\hat{\eta}$s in Figure 6, captured the oscillation behavior as soon as it exceeded the limit. It explains the promptness of proposed detector. The external disturbance with short oscillating period is detected much earlier than the principal oscillation. Moreover, it proved that the clustering procedure of $\hat{\eta}$ increased the robustness in detecting oscillation mode in noisy PRC y_1^1.

Case 2. The second case presents a process variable with time-variant frequency and amplitude. $y_2(n)$ is collected from a loop with decreasing performance due to a sticky

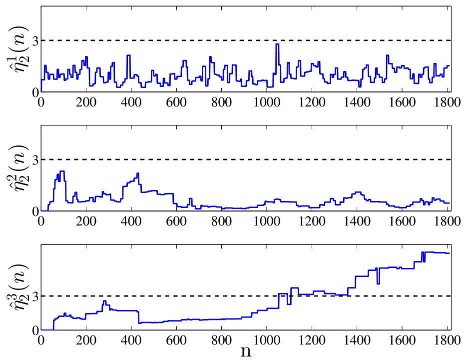

Fig. 8. Oscillation monitoring charts on Case 2

valve. It illustrates the effectiveness of the proposed oscillation detector in monitoring the slowly growing oscillatory data. The time trend of $y_2(n)$ is shown on top of Figure 7. The valve was operating in good condition at first. In n=200, some failure in the control valve may occur, leading to a larger variance of the process variable. During n=200-700, the sticky action of valve is gradually more serious with growing amplitudes of oscillation. The stiction with its non-linear behavior can be visually discovered. The monitoring procedure is presented in Figure 8. The principal PRC of $y_2(n)$ is extracted and confirmed to be oscillatory successfully.

6. CONCLUSIONS

This paper introduced a real-time oscillation detector technique with an modified Intrinsic Time-scale Decomposition. Modified ITD automatically decomposes the real-time measurement into several proper rotation components and a non-oscillating residual. ITD preserves the non-linearity features of the data. The detector enables rapid computation for online applications. Hypothesis test is revised with clustered $\hat{\eta}$ provides a robust monitor to the unexpected behaviors. It is prompt to individually detect multiple oscillations. A numerical example and case studies verified the detector in monitoring process variable of time-variant features. It is promising to utilize the detector to measure how the oscillation behaves in industrial loops.

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