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A Systematic Approach to Dynamic Monitoring of Industrial Processes Based on Second-Order Slow Feature Analysis ⋆

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Abstract: Slow feature analysis has proven to be an effective process monitoring and fault diagnosis approach. By isolating temporal behaviors from steady-state variations in process data, slow feature analysis enables a concurrent monitoring of operating condition and process dynamics, based on which false alarms triggered by nominal operating condition deviations can be effectively removed. However, the present formulation of slow feature analysis only makes use of the first-order time difference of time series data, thereby falling short of addressing high-order dynamics in process operations. In this work, we propose a second-order formulation of slow feature analysis, and further develop a systematic framework for process monitoring and fault diagnosis, which can provide more meaningful information about process dynamics to assist decision-making of operators. Case studies on the Tennessee Eastman benchmark process are conducted to demonstrate the efficacy of the proposed method.

Keywords: Process monitoring, fault diagnosis, slow feature analysis, latent variable models.

1. INTRODUCTION

In the past decade, more and more data have been measured and collected in process industries due to the rapid development of information technology. At the same time, machine learning and data mining provide methodological supports for data-driven monitoring approaches in process industries. By analyzing inherent patterns within process data collected under nominal conditions, process monitoring methods and systems have been effectively developed in academia and industry, with the aim to identify whether the process is operating normally (Qin (2012); Severson et al. (2016)). In essence, process monitoring is performed by checking the similarity between current process variable measurements and historical data, which is evaluated by various statistical models, such as principal component analysis (PCA), partial least squares (PLS), and independent component analysis (ICA).

Under the compensation of feedback control systems, the process could probably arrives at a new yet acceptable operating condition. In such occasion, the alarms triggered by monitoring systems are essentially superfluous and hence shall be eliminated timely (Qin (2012)). Otherwise, a large amount of labor costs will be induced, especially when such operating condition deviations occur frequently (Gao et al. (2016)). Unfortunately, this issue has not been addressed by classic process monitoring approaches such as PCA, PLS, and ICA.

Based on such motivations, slow feature analysis (SFA), an emerging dimension reduction approach in pattern recognition, has been employed for a comprehensive monitoring of working points and process dynamics recently (Shang et al. (2015b, 2016, 2018); Guo et al. (2016)). An exclusive merit of SFA is that it enables simultaneous descriptions of both the steady distribution $P(\mathbf{x})$ and the temporal distribution $P(\dot{\mathbf{x}})$ of process variables. The temporal distribution $P(\dot{\mathbf{x}})$ provides an effective indicator of process dynamics and control performance, while being immunized against frequent operating condition deviations.

In the era of big data, more and more attention have been paid to generalization ability and interpretability of features in machine learning models, which motivate a new concept termed as *representation learning* (Bengio et al. (2013); Qin (2014)). It states that, a good feature learnt from data shall bear clear physical interpretations, and generalize well on out-of-sample data. In this way, more reliable model performance and more rational data-driven decisions can be attained. Application results of SFA on process data analytics indicate that, SFA well exemplifies the concept of representation learning, since slow features enable an effective characterization of process dynamics (Shang et al. (2015a)). Most importantly, they remain valid under different nominal operating conditions (Shang et al. (2015b)), implying that SFA could capture the inherent physical mechanism of industrial processes under closed-loop control with effect.

In the existing SFA-based monitoring scheme, only first-order dynamics underlying processes is modeled and monitored because it is defined based on the first-order time

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difference of time series data. To furnish more meaningful information to assist decision-making of process operators, high-order dynamics of process variables should be further taken into considerations, thereby providing a comprehensive picture about process dynamic behaviors. To this end, we propose a novel second-order SFA model as well as the associated monitoring strategy in this article. We first derive new features based on a generalized measure of slowness, which is defined based on second-order time difference of time series data. Based on that, we devise two novel statistics for monitoring high-order dynamics of process variables. We propose that these two new statistics are not contradictory to the generic SFA-based monitoring scheme. Instead, they shall be used as a whole to furnish more meaningful monitoring information. We discuss how to interpret alarm information raised by different monitoring statistics, and further investigate its exclusive usage in evaluating the severity of dynamics anomalies. The empirical performance of the proposed monitoring approach is testified on the Tennessee Eastman (TE) benchmark process in comparison with the classic PCA-based monitoring approach.

The layout of this paper is organized as follows. Section 2 reviews basics of slow feature analysis and the associated monitoring scheme in brief. A new dimension reduction approach termed as second-order SFA is proposed in Section 3, along with two novel statistics for monitoring high-order dynamics of industrial processes. Section 4 reports the results of case studies on the TE benchmark process. Finally concluding remarks are drawn.

2. PRELIMINARIES

2.1 Conventional SFA

The optimization problem of SFA can be formally described as follows (Wiskott and Sejnowski (2002)). Given an m-dimensional input signal $\mathbf{x}(t) \in \mathbb{R}^m$, find m instantaneous mappings from inputs to slow features $s_i(t) = \mathbf{w}_i^{\mathrm{T}}\mathbf{x}(t)$ $(1 \le i \le m)$, such that

$$\Delta(s_i) := \langle \dot{s}_i^2 \rangle_t \tag{1}$$

is minimal, under the constraints

$$\langle s_i \rangle_t = 0, \ \text{(zero mean)} \tag{2}$$

$$\langle s_i^2 \rangle_t = 1, \ \text{(unit variance)} \tag{3}$$

$$\forall i \neq j, \ \langle s_i s_j \rangle_t = 0, \ \text{(decorrelation and order)} \tag{4}$$

where $\langle \cdot \rangle_t$ and $\dot{s}(t) = s(t) - s(t-1)$ denote, respectively, time averaging and first-order time difference of s. Given N historical samples $\{u(1), \cdots, u(N)\}$, the time averaging of a certain signal u is empirically calculated as:

$$\langle u \rangle_t = \frac{1}{N}\sum_{t=1}^{N} u(t). \tag{5}$$

The objective (1) encourages each slow feature to have as slow variations as possible. The introduction of constraints (2) and (3) helps excluding the trivial constant solution, whereas constraint (4) enforces different slow features to incorporate different information. For more details readers are referred to Shang et al. (2015b).

If each dimension of input $\mathbf{x}(t)$ has been scaled to zero mean, the solution to the above optimization problem can be recast as a generalized eigenvalue decomposition (GED) (Wiskott and Sejnowski (2002)):

$$\mathbf{R}_{\dot{\mathbf{x}}\dot{\mathbf{x}}}\mathbf{W} = \mathbf{R}_{\mathbf{xx}}\mathbf{W}\boldsymbol{\Omega} \tag{6}$$

where $\mathbf{R}_{\dot{\mathbf{x}}\dot{\mathbf{x}}} = \langle \dot{\mathbf{x}}\dot{\mathbf{x}}^{\mathrm{T}} \rangle_t$ and $\mathbf{R}_{\mathbf{xx}} = \langle \mathbf{x}\mathbf{x}^{\mathrm{T}} \rangle_t$ denote covariance matrices of $\dot{\mathbf{x}}$ and $\mathbf{x}$, respectively; $\mathbf{W} = [\mathbf{w}_1, \cdots, \mathbf{w}_m]$ is the matrix of m generalized eigenvectors, which stand for coefficient vectors of m linear mappings; $\boldsymbol{\Omega} = \mathrm{diag}\{\omega_1, \cdots, \omega_m\}$ contains generalized eigenvalues on its diagonal, which satisfy $\omega_i = \langle \dot{s}_i^2 \rangle_t$ and are arranged in an ascending order. This makes the slowest features have the lowest indices.

2.2 Solution to the Generalized Eigenvalue Problem

Resolving the GED (6) requires two consecutive eigen-decompositions (Jennings and McKeown (1992)). Assuming that the covariance matrix $\mathbf{R}_{\mathbf{xx}}$ decomposes as $\mathbf{R}_{\mathbf{xx}} = \mathbf{U}\boldsymbol{\Lambda}\mathbf{U}^{\mathrm{T}}$ in the first step, one obtains

$$\mathbf{R}_{\dot{\mathbf{x}}\dot{\mathbf{x}}}\mathbf{W} = \mathbf{U}\boldsymbol{\Lambda}\mathbf{U}^{\mathrm{T}}\mathbf{W}\boldsymbol{\Omega}. \tag{7}$$

The first step is also known as *sphering*. Denoting the sphering matrix $\mathbf{Q} = \boldsymbol{\Lambda}^{-\frac{1}{2}}\mathbf{U}^{\mathrm{T}}$ in shorthand, (7) can be recast as:

$$\mathbf{Q}\mathbf{R}_{\dot{\mathbf{x}}\dot{\mathbf{x}}}\mathbf{Q}^{\mathrm{T}}(\mathbf{Q}^{-\mathrm{T}}\mathbf{W}) = (\mathbf{Q}^{-\mathrm{T}}\mathbf{W})\boldsymbol{\Omega}. \tag{8}$$

Therefore, performing eigen-decomposition on the sphered covariance matrix $\mathbf{Q}\mathbf{R}_{\dot{\mathbf{x}}\dot{\mathbf{x}}}\mathbf{Q}^{\mathrm{T}} = \mathbf{P}\boldsymbol{\Omega}\mathbf{P}^{\mathrm{T}}$ in the second step yields the final solution to (6), i.e., $\mathbf{W} = \mathbf{Q}^{\mathrm{T}}\mathbf{P}$.

2.3 Monitoring Statistics Design

According to the slowness value $\{\omega_i\}$, slow features can be classified as *dominant features* $\mathbf{s}_d \in \mathbb{R}^M$ having slow variations, and *residual features* $\mathbf{s}_e \in \mathbb{R}^{m-M}$ having fast variations (Shang et al. (2015b)), where M denotes the number of dominant features. Then the following two pairs of monitoring charts are defined for distinct purposes.

For monitoring operating condition deviations, that is, the violation of static distribution $P(\mathbf{x})$, the first pair of statistics is defined as follows:

$$T^2 = \mathbf{s}_d^{\mathrm{T}}\mathbf{s}_d = \mathbf{x}^{\mathrm{T}}(t)\mathbf{Q}^{\mathrm{T}}\mathbf{P}_d^{\mathrm{T}}\mathbf{P}_d\mathbf{Q}\mathbf{x}(t), \tag{9}$$

$$\begin{aligned} T_e^2 = \mathbf{s}_e^{\mathrm{T}}\mathbf{s}_e &= \mathbf{x}^{\mathrm{T}}(t)\mathbf{Q}^{\mathrm{T}}\mathbf{P}_e^{\mathrm{T}}\mathbf{P}_e\mathbf{Q}\mathbf{x}(t) \\ &= \mathbf{x}^{\mathrm{T}}(t)\mathbf{Q}^{\mathrm{T}}(\mathbf{I} - \mathbf{P}_d^{\mathrm{T}}\mathbf{P}_d)\mathbf{Q}\mathbf{x}(t), \end{aligned} \tag{10}$$

where $\mathbf{P} = [\mathbf{P}_d \ \mathbf{P}_e]$. Matrices $\mathbf{P}_d$ and $\mathbf{P}_e$ contains eigenvectors with respect to, respectively, M minor eigen-values and $M_e = m - M$ principal eigen-values.

For monitoring process dynamics anomalies, that is, the violation of temporal distribution $P(\dot{\mathbf{x}})$, the second pair of statistics is defined as follows (Shang et al. (2015b)):

$$S^2 = \dot{\mathbf{s}}_d^{\mathrm{T}}\boldsymbol{\Omega}_d^{-1}\dot{\mathbf{s}}_d = \dot{\mathbf{x}}^{\mathrm{T}}(t)\mathbf{Q}^{\mathrm{T}}\mathbf{P}_d^{\mathrm{T}}\boldsymbol{\Omega}_d^{-1}\mathbf{P}_d\mathbf{Q}\dot{\mathbf{x}}(t), \tag{11}$$

$$S_e^2 = \dot{\mathbf{s}}_e^{\mathrm{T}}\boldsymbol{\Omega}_e^{-1}\dot{\mathbf{s}}_e = \dot{\mathbf{x}}^{\mathrm{T}}(t)\mathbf{Q}^{\mathrm{T}}\mathbf{P}_e^{\mathrm{T}}\boldsymbol{\Omega}_e^{-1}\mathbf{P}_e\mathbf{Q}\dot{\mathbf{x}}(t), \tag{12}$$

where

$$\boldsymbol{\Omega}_d = \mathrm{diag}\{\omega_1, \cdots, \omega_M\}, \tag{13}$$

$$\boldsymbol{\Omega}_e = \mathrm{diag}\{\omega_{M+1}, \cdots, \omega_m\}. \tag{14}$$

The principle behind the SFA-based monitoring scheme in Shang et al. (2015b) can be illustrated as follows. A simultaneous utilization of two pairs of statistics furnishes comprehensive knowledge about the process status. For instance, once T^2 or T_e^2 statistic declares deviations from design conditions, one can further count on S^2 and S_e^2 statistics to understand the process status. If the process still gets well controlled, there will be no dynamics disruption and then S^2 and S_e^2 statistics should be normally valued. In case of real faults that are irrecoverable via control systems, dynamics anomalies probably show up, and S^2 and S_e^2 statistics suffice to deliver adequate information.

3. SECOND-ORDER SLOW FEATURE ANALYSIS FOR PROCESS MONITORING

3.1 Dimension reduction with second-order SFA

In the original formulation of SFA, the slowness $\Delta(s)$ of a certain signal $s(t)$ is defined based on the first-order time difference $\dot{s}(t)$. If we turn to the second-order time difference

$$\begin{aligned}\ddot{s}(t) &= \dot{s}(t) - \dot{s}(t-1) \\ &= s(t) - 2s(t-1) + s(t-2)\end{aligned} \tag{15}$$

to measure how fast a signal varies, then the optimization objective of the induced SFA model is to minimize

$$\Delta(s_i) := \langle \ddot{s}_i^2 \rangle_t \tag{16}$$

subject to the constraints

$$\langle s_i \rangle_t = 0, \ \text{(zero mean)} \tag{17}$$

$$\langle s_i^2 \rangle_t = 1, \ \text{(unit variance)} \tag{18}$$

$$\forall i \neq j, \ \langle s_i s_j \rangle_t = 0, \ \text{(decorrelation and order)} \tag{19}$$

We call this model *second-order SFA*. Similar to the generic SFA, the resulting optimization problem can also be cast as a GED:

$$\mathbf{R}_{\ddot{\mathbf{x}}\ddot{\mathbf{x}}}\mathbf{W} = \mathbf{R}_{\mathbf{x}\mathbf{x}}\mathbf{W}\mathbf{\Omega}. \tag{20}$$

After solving the GED, a small portion of slow features will be designated as dominant feature carrying most information. The number of dominant features M can be determined based on the reconstruction criterion developed by Shang et al. (2015b).

Notice that we can still add some lagged variables to the input of the second-order SFA model, in a similar spirit to dynamic PCA (DPCA) (Ku et al. (1995)):

$$\mathbf{x}(t) \triangleq \begin{bmatrix} \mathbf{x}(t) \\ \mathbf{x}(t-1) \\ \vdots \\ \mathbf{x}(t-d) \end{bmatrix} \in \mathbb{R}^{m(d+1)}, \tag{21}$$

where d stands for the length of lagged data. The resulting model is referred to as dynamic SFA (DSFA).

3.2 A holistic process monitoring scheme design

Based on the solution to GED (20), we can also define two groups of monitoring statistics to detect disruptions of distributions $P(\mathbf{x})$ and $P(\ddot{\mathbf{x}})$. We are more interested in the latter one because the steady distribution $P(\mathbf{x})$ has already been described by first-order SFA. Therefore, we only define two new monitoring statistics, termed as SS^2 and SS_e^2, to identify potential anomalies in second-order temporal dynamics:

$$SS^2 = \ddot{\mathbf{s}}_d^{\mathrm{T}}\mathbf{\Omega}_d^{-1}\ddot{\mathbf{s}}_d = \ddot{\mathbf{x}}^{\mathrm{T}}(t)\mathbf{Q}^{\mathrm{T}}\mathbf{P}_d^{\mathrm{T}}\mathbf{\Omega}_d^{-1}\mathbf{P}_d\mathbf{Q}\ddot{\mathbf{x}}(t), \tag{22}$$

$$SS_e^2 = \ddot{\mathbf{s}}_e^{\mathrm{T}}\mathbf{\Omega}_e^{-1}\ddot{\mathbf{s}}_e = \ddot{\mathbf{x}}^{\mathrm{T}}(t)\mathbf{Q}^{\mathrm{T}}\mathbf{P}_e^{\mathrm{T}}\mathbf{\Omega}_e^{-1}\mathbf{P}_e\mathbf{Q}\ddot{\mathbf{x}}(t). \tag{23}$$

The control limits for SS^2 and SS_e^2 statistics can be derived in a similar spirit to those for S^2 and S_e^2, which are given by (Shang et al. (2015b)):

$$SS_\alpha^2 = \frac{M(N-1)(N-3)}{(N-2)(N-M-2)}F_{M,N-M-2,\alpha}, \tag{24}$$

$$SS_{e,\alpha}^2 = \frac{M_e(N-1)(N-3)}{(N-2)(N-M_e-2)}F_{M,N-M_e-2,\alpha}, \tag{25}$$

where α denotes the confidence level, and $F_{a,b,\alpha}$ stands for the α-quantile value of the F-distribution with a and b degrees of freedom.

We propose to use these two new statistics in conjunction with four statistics induced by generic SFA together, which yields a holistic process monitoring scheme design. Table 1 summarizes three groups of monitoring statistics and their usage in practice. Compared to the original SFA-based monitoring approach, the proposed approach involves two additional statistics for monitoring high-order dynamics anomalies, which provides more monitoring information. How to interpret the information conveyed by SS^2 and SS_e^2 statistics needs some careful considerations.

Table 1. A Summary of Proposed Monitoring Statistics

Statistics	Usage
T^2 and T_e^2	Detection of steady working point changes
S^2 and S_e^2	Detection of first-order dynamics anomalies
SS^2 and SS_e^2	Detection of second-order dynamics anomalies

Notice that the S^2 and S_e^2 statistics enjoy insensitivity to operating condition deviations because the first-order time difference eliminates the effect of steady working points. Similar to the S^2 and S_e^2 statistics, SS^2 and SS_e^2 statistics can also be conceived as characterizing nominal control performance (Shang et al. (2016)), and hence can be used for detecting and diagnosing alterations in control performance. If the process is operating normally at a newly reached working point with control performance unaffected, then four statistics pertaining to dynamics, namely S^2, S_e^2, SS^2 and SS_e^2, will be normally valued. If S^2 and S_e^2 statistics indicate nominal control performance at a new working point, then the proposed SS^2 and SS_e^2 statistics can be used to further acknowledge this conclusion to improve its reliability.

Moreover, thanks to the invariant nature of the second-order time difference, the SS^2 and SS_e^2 statistics are insensitive to not only operating condition deviations but also first-order dynamics anomalies. When the process is shifting towards a new operating point with a constant velocity, then both $P(\mathbf{x})$ and $P(\dot{\mathbf{x}})$ of nominal data will be violated. On such occasion, SS^2 and SS_e^2 tend to be normally valued because the distribution of second-order dynamics $P(\ddot{\mathbf{x}})$ remains intact. This is the just case of some mild and incipient faults, which will be immunized against by two new statistics. If the fault evolves with an abruptly varying velocity, severe dynamics anomalies will be induced. Under such circumstance, SS^2 and SS_e^2 will probably go beyond their thresholds and hence trigger alarms continuously. In this sense, SS^2 and SS_e^2 statistics embody more meaningful information about the *severity* of dynamics anomalies.

To summarize, three groups of monitoring charts basically feature *a hierarchy of alarm significance*. When S^2 and S_e^2 statistics are normal, the information brought by SS^2 and SS_e^2 statistics can help further acknowledge whether process dynamics is unaffected. Moreover, when S^2 and S_e^2 statistics exceed their thresholds, we can further resort to SS^2 and SS_e^2 statistics to assess whether the dynamics anomalies is mild or severe. In this way, process operators can have a clearer picture about the significance of abnormal events, quickly identify the type of the fault, make rational decisions and take in-time maintenance measures.

4. CASE STUDIES ON THE TENNESSEE EASTMAN PROCESS

In this section, we carry out case studies based on the TE process (Downs and Vogel (1993)), which is a widely accepted benchmark for quantifying performances of different monitoring approaches. The plant-wise control strategy proposed by Lyman and Georgakis (1995) is employed here, in which the agitation speed XMV(12) is not manipulated and thus excluded from monitored variables. There are 33 process variables selected as monitored variables, including 11 manipulated variables XMV(1-11) and 22 measured variables XMEAS(1-22), whose sampling interval is set as 3 min. Under nominal condition, 500 data samples are collected in total for building monitoring models. For a comprehensive comparison, we adopt two approaches, i.e. DPCA and second-order DSFA combined with generic DSFA, to establish monitoring models, with $d = 2$ lagged variables added to the input according to (21). The PRESS statistic is utilized here to determine the number of principal components in the DPCA model (Valle et al. (1999)). The confidence levels for all derived control limits are set to $\alpha = 99\%$. Next, we make a comprehensive investigation into three representative faulty scenarios of the TE process, where the disturbances/faults occur at the 160th sample.

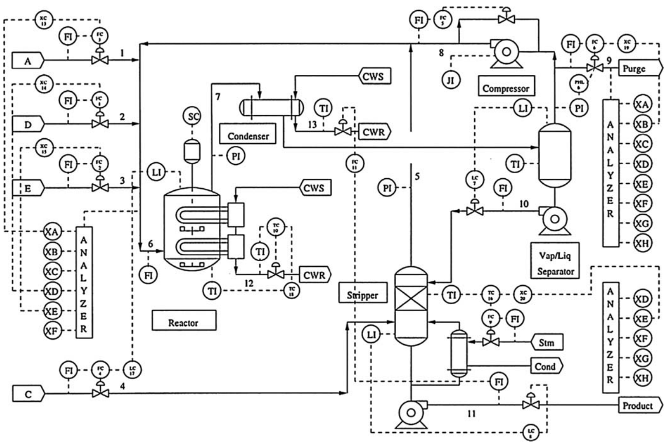


Fig. 1. Architecture of the TE benchmark process (Lyman and Georgakis (1995))

IDV(1): Step disturbance in A/C feed ratio

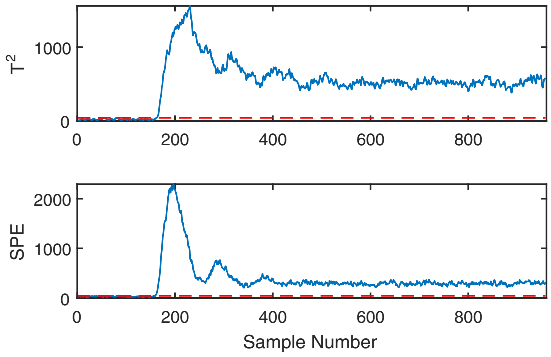
In this case, a minor change in A/C feed ratio is introduced, which primarily affects the mass balance and the reflux of the entire process. However, after short-lived compensation behaviors of the plant-wide controllers, the process can reach a new operating condition with nominal dynamics (Shang et al. (2015b)). Fig. 2 showcases the monitoring results of two methods. We can see that DPCA only indicates that some abnormal events have occurred, and it is difficult to have an in-depth illustration of the information behind the T^2 and SPE statistics in Fig. 2(a). By contrast, the proposed method provides a comprehensive picture about the anomaly. On one hand, T^2 and T_e^2 statistics in Fig. 2(b) showcase that a new steady operating condition has been created. On the other hand, the S^2 statistic exceeds its limit shortly and recovers around the 400th sample, clearly revealing the beginning and the ending of compensation behaviors of controllers. In this sense, the alarms triggered by T^2 and T_e^2 statistics can be indeed removed after the S^2 statistic returns to normal. What's more, the SS^2 statistic further shows that, the compensation behavior becomes more abrupt after the 220th sample because of the occurrence of several peaks. And after the 400th sample, both SS^2 and SS_e^2 provide useful information to confirm that the process has again a nominal control performance. From this example, it can be seen that in comparison with generic DPCA-based method, the proposed approach could furnish much more meaningful monitoring information for process operators.

Meanwhile, we observe that during compensations, S_e^2 and SS_e^2 statistics have much slighter perturbations than S^2 and SS^2 statistics. This is because S_e^2 and SS_e^2 statistics are defined based on slow features with fast noisy variations, and hence are less sensitive to dynamics anomalies. It implies that *slowness* is a reasonable principle to extract *driving factors* behind process variables. Because of this, the subspace with primary slowly-varying variations will be more easily violated by dynamics anomalies, as is detected by S^2 and SS^2 statistics.

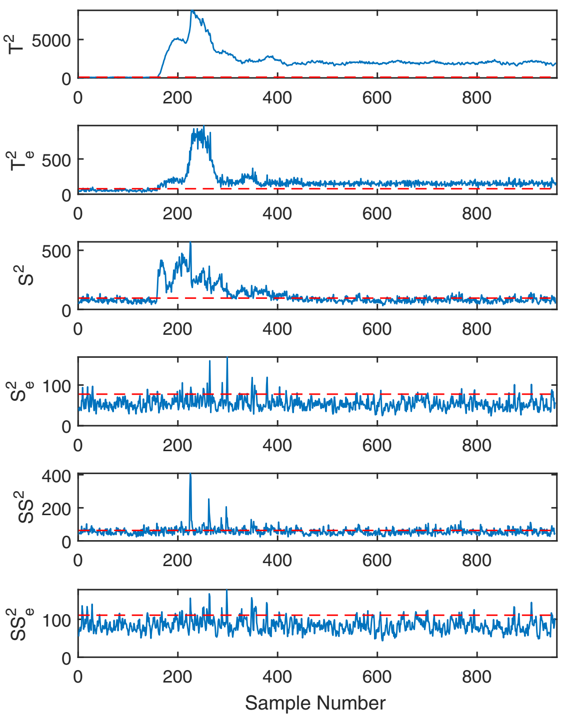
IDV(4): Step disturbance in reactor cooling water inlet temperature

In this scenario, a step disturbance is introduced in reactor cooling water inlet temperature, which may affect the reactor temperature XMEAS(9). Fig. 1 displays that a cascade controller is responsible for maintaining the reactor temperature by adjusting the reactor water flow XMV(10). It is known that this fault can be rapidly mitigated by this cascade controller (Shang et al. (2015b)). The corresponding monitoring results are reported in Fig. 3. We can see that DPCA can detect this fault via the SPE statistic. By contrast, the proposed method could not only detect operating condition deviation by means of the T^2 statistic, but also highlight that process dynamics and control performance recover rapidly after short adjustment of feedback controllers. Therefore, there is no need to worry about the operating condition deviation, and the alarm shall be removed to avoid potential manual examinations. Compared to the generic SFA-based monitoring approach, the extra information given by SS^2 and SS_e^2 statistics enhances the reliability of decisions of removing alarms.

Moreover, this case well demonstrates that slowness characteristics learnt by the SFA model can have remarkable generalization ability because they remain unaffected at a completely different working point. It implies that slow features can well represent fundamental driving factors



(a) DPCA



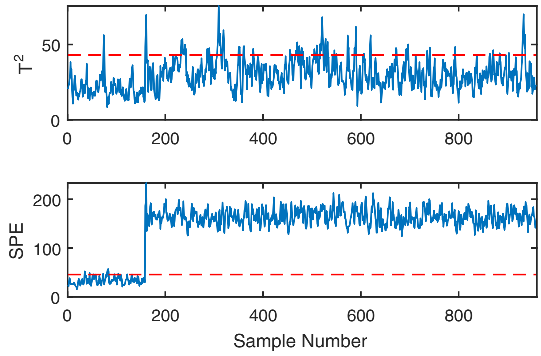
(b) The proposed method

Fig. 2. Monitoring results for a step disturbance in A/C feed ratio.

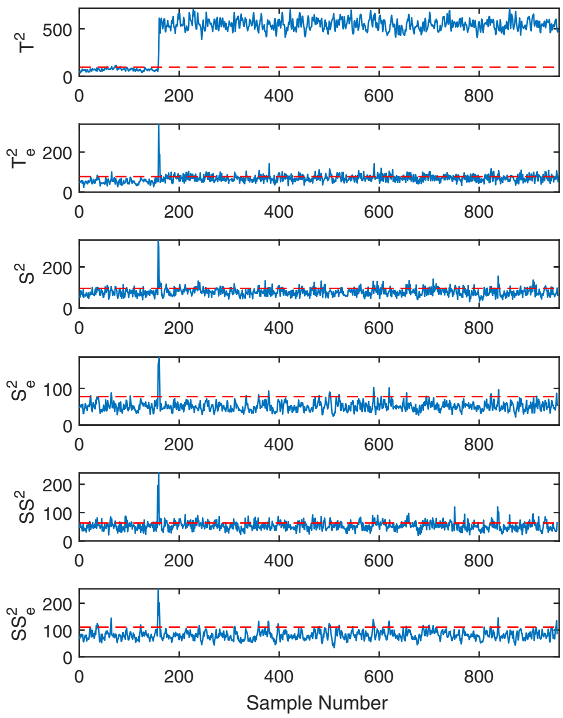
of industrial processes, being in line with the spirit of representation learning.

IDV(13): Slow drift in reaction kinetics

In this case, reaction kinetics experience a slow drift till the end, which gradually disrupts the control performance. Monitoring results are given in Fig. 4. We can see that DPCA can detect this fault after the 200th sample. The SFA-based approach is more sensitive than DPCA because T_e^2 and S^2 statistics go beyond control limits before the 200th sample. Most importantly, it can well characterize the pattern of this abnormal events. Notice that at the beginning stage of this fault (160th - 400th sample), the S^2 statistic indicates first-order dynamics anomalies, while SS^2 and SS_e^2 statistics are still below their limits. As aforementioned, we can deduce that *this is probably a mild and incipient fault*, which is particularly beneficial for the operator to recognize the fault type and update catalyst in time before a worse condition is reached. After the 400th sample, the reaction kinetics is insufficient such that even the second-order dynamics is altered, indicating the control performance becomes significantly different from the nominal case. This case well demonstrates the advantage of the proposed method in determining a mildly evolving fault at its early stage by utilizing different information conveyed by different statistics.



(a) DPCA

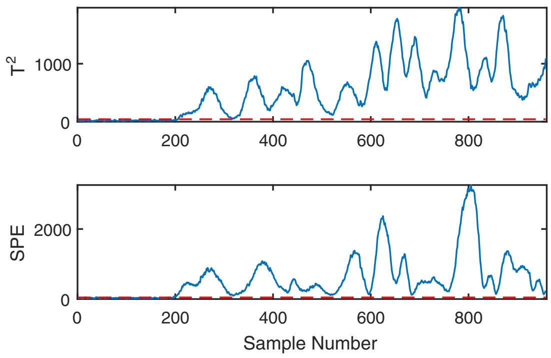


(b) The proposed method

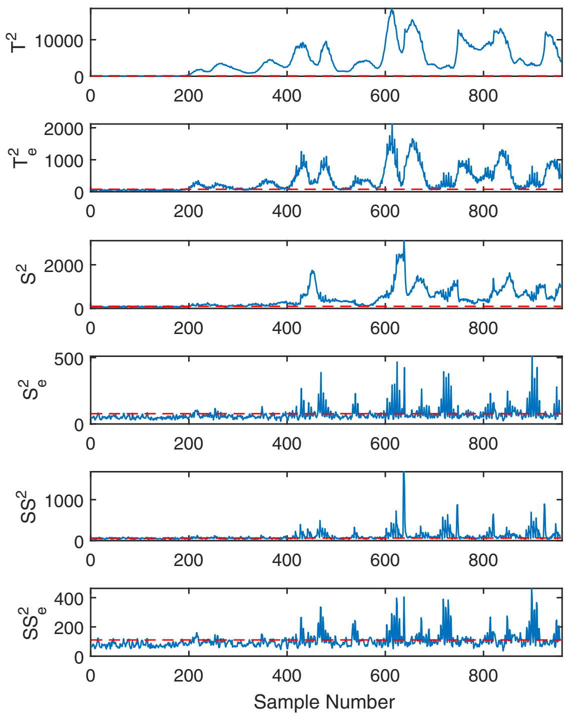
Fig. 3. Monitoring results for a step disturbance in reactor cooling water inlet temperature.

5. CONCLUSION

In this article, we develop a second-order version of SFA and two novel statistics to monitor high-order dynamic behaviors of industrial processes, which provide abundant



(a) DPCA



(b) The proposed method

Fig. 4. Monitoring results for a slow drift in reaction kinetics.

information for process operators to understand the operating situation, remove potential false alarms, and distinguish the type of the fault. We propose a new measure of slowness of variations based on second-order time difference of process variables to formulate SFA models, based on which two novel monitoring statistics are put forward to detect high-order dynamics anomalies within industrial processes. These two statistics are used in conjunction with the generic SFA-based monitoring approach, yielding a systematic monitoring paradigm with hierarchical monitoring statistics. We show by the TE benchmark process that the proposed method is not only effective in eliminate false alarms induced by nominal operating point changes, but also advantages in evaluating the severity of dynamics anomalies, especially in determining the mildly evolving fault as early as possible. Although the current formulation is second-order, it can be easily extended to high-order cases to provide more information about process dynamics.

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