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The Automatic Analytics Framework for Multiple Oscillations in the Coupled Control Loops via a New Variant of Slow Feature Analysis

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Abstract: Oscillation is a frequent type of control performance degradation in the process. Multiple oscillations may propagate in the coupled control loops, bringing challenges to detection and localization of oscillations. In this paper, a time-frequency analysis framework including detection, extraction, and localization of oscillations is proposed. The method is based on a new variant of slow feature analysis (SFA), termed multi-lag derivatives dynamic slow feature analysis (MDSFA), and a new indicator, termed oscillation matched degree (OMD). To detect and reveal the possible oscillation sources, MDSFA is proposed to extract features with different rates from the observed data and probe into the time-delay effect and multi-lag autocorrelations specific to control loops. To pinpoint the root loops and travel paths of oscillations, the OMD indicator is designed via the spectral analysis, which can measure the oscillation frequencies and amplitudes. The proposed method is verified to be able to detect and locate oscillations automatically and efficiently via the real thermal power process.

Keywords: Oscillations, slow feature analysis, time-delay effect, one-lag autocorrelation, coupled control loops, control performance monitoring, spectral analysis, oscillation propagation.

1. INTRODUCTION

In modern industries, the routine monitoring of control performance has been increasingly recognized as a critical way to maintain the process at the predesigned operating conditions, safely and efficiently (Zhao et al. 2018). Among the multiple aspects of control performance monitoring, oscillation analytics has drawn considerable attention due to its high incidence and corrupted impacts on plant profitability and safety (Dambros et al. 2019).

The causes of oscillations are not limited to poorly designed controllers, non-linearities, and external disturbances (Jelali et al. 2009). Multiple oscillations may propagate in the coupled loops through the direct connections, energy transfer, and flow paths. Detection and isolation of oscillations are critical. The relevant research can be summarized into three categories: (i) developing time-domain criteria such as integral absolute error (IAE) based rules (Hägglund et al. 1995, Thornhill et al. 1997) and auto-correlation function (ACF) approach (Miao et al. 1999), (ii) performing signal processing like multivariate empirical mode decomposition (MEMD) method (Aftab et al. 2018), GA based factorization (El-Ferik et al. 2012), and wavelet transform method (Naghoosi et al. 2017), (iii) employing spectral analysis (Xia et al. 2005, Jiang et al. 2007, Xu et al. 2016).

With the development of machine learning (ML) techniques, another group of methods has been explored for fault detection over the last two decades. However, few ML-based methods (Zabiri et al. 2009, Dambros et al. 2019) have been published for oscillation analytics. Recently, slow feature analysis (SFA) (Berkes et al. 2005) is widely applied to the process monitoring (Zhang et al. 2019) with extraction of slowly-varying features (SFs) from the time series data (Zheng et al. 2019). SFA is appropriate to oscillation detection for the following characteristics: (i) As SFA aims at minimizing the slowness of features, multiple oscillations can be extracted because most oscillations in control loops have low frequencies owing to the long settling time of most controllers (Gao et al. 2015). (ii) Being able to separate signals with different rates (Yu et al. 2018), SFA is helpful to separate multiple oscillations with different periods. (iii) Another interpretation of SFA is to find a set of mappings, such that the outputs have the largest one-lag autocorrelations. It in a sense eliminates the disturbances of white noise whose one-lag autocorrelation is zero.

However, the original SFA does not consider the time-delay effect which results from the long settling time of controllers and the hysteresis of processes. Moreover, as SFA only focuses on the one-lag temporal derivative, it does not cover other derivatives with different lags which may also reflect characteristics of oscillations. In summary, three important problems should be addressed: (i) How to detect and extract multiple oscillations in the coupled control loops with SFA? (ii) How to localize root loops and pinpoint travel paths of multiple oscillations? (iii) How to consider the influence of the time-delay effect and multi-lag temporal derivatives?

In this paper, to consider the time-delay effect and cover the multi-lag temporal derivatives, the multi-derivative dynamic slow feature analysis, termed MDSFA here, is proposed for extracting multiple oscillations hidden in the observed data.

Besides, as spectral analysis (Nussbaumer 1981) can give some power information of oscillations and eliminate the disturbance of oscillations with the same frequency but different phases, a new index, termed oscillation matched degree (OMD) is proposed. It is a useful reference to reveal the root loops and travel paths of multiple oscillations.

The remainder of this paper is organized as follows. First, brief methods preliminaries are given in Section 2. In Section 3, the proposed MDSFA and an automatic analytics scheme for oscillations are presented in detail. After that, a case study is shown to verify the performance of the proposed method in Section 4. Finally, some conclusions are drawn in Section 5.

2. METHODS PRELIMINARIES

2.1 SFA

For the given process data $\mathbf{x}(t)=\left[\mathbf{x}_1(t),\mathbf{x}_2(t),\ldots,\mathbf{x}_M(t)\right]^{\mathrm{T}}$, the original SFA aims at finding a set of transform functions $\mathrm{g}(\mathbf{x})=\{\mathrm{g}_1(\mathbf{x}),\mathrm{g}_2(\mathbf{x}),\ldots,\mathrm{g}_M(\mathbf{x})\}$, such that the extracted features can vary as slowly as possible. The features can be obtained by $\mathbf{s}_j(t)=\mathrm{g}_j(\mathbf{x}(t))$, and J SFs are denoted as $\mathbf{s}_j(t)(j=1,2,\ldots,J)$, ranked from the slowest to the fastest. The above target can be realized by (1), where $\langle\cdot\rangle_t$ denotes the time averaging, calculated as in (2). The one-lag temporal derivative of $\mathbf{s}_j$ is denoted as $\dot{\mathbf{s}}_j$, calculated as in (3).

$$\min\left\langle \dot{\mathbf{s}}_j^{\,2}\right\rangle_t \tag{1}$$

$$\left\langle \mathbf{s}_j\right\rangle_t=\frac{1}{t_1-t_0}\int_{t_0}^{t_1}\mathbf{s}_j(t)dt \tag{2}$$

$$\dot{\mathbf{s}}_j(t)\approx\frac{\mathbf{s}_j(t)-\mathbf{s}_j(t-\Delta t)}{\Delta t} \tag{3}$$

The following three constraints should be kept to normalize the features, avoid trivial constant solutions, and force the extracted features to be uncorrelated with each other.

$$\left\langle \mathbf{s}_j\right\rangle_t=0 \tag{4}$$

$$\left\langle \mathbf{s}_j^{\,2}\right\rangle_t=1 \tag{5}$$

$$\forall i<j,\left\langle \mathbf{s}_i\mathbf{s}_j\right\rangle_t=0 \tag{6}$$

For linear SFA, features can be calculated simply as a linear combination of columns of the observed data as in (7), where $\mathbf{W}=\left[w_1,w_2,\ldots,w_M\right]^{\mathrm{T}}$ is the transform matrix.

$$\mathbf{s}=\mathbf{WX} \tag{7}$$

The solution of linear SFA can be easily derived by solving the generalized eigenvalue problem of the one-lag temporal derivative of data.

2.2 Dynamic SFA

A simple extension of SFA is dynamic SFA (DSFA), which is proposed to consider the process dynamics (Zheng et al. 2019). DSFA has been widely used in the field of chemical processes with typical dynamics. The basic idea is to include previous measurements to construct an augmented matrix $\overline{\mathbf{X}}$. The input matrix with N available samples can be stacked as in (8) by augmenting the original data with d lagged samples.

$$\overline{\mathbf{X}}=\begin{bmatrix}\mathbf{x}(t)^{\mathrm{T}} & \mathbf{x}(t-1)^{\mathrm{T}} & \cdots & \mathbf{x}(t-d)^{\mathrm{T}}\\ \mathbf{x}(t+1)^{\mathrm{T}} & \mathbf{x}(t)^{\mathrm{T}} & \cdots & \mathbf{x}(t-d+1)^{\mathrm{T}}\\ \vdots & \vdots & \ddots & \vdots\\ \mathbf{x}(t+N-1)^{\mathrm{T}} & \mathbf{x}(t+N-2)^{\mathrm{T}} & \cdots & \mathbf{x}(t+N-d-1)^{\mathrm{T}}\end{bmatrix} \tag{8}$$

The solution of DSFA is the same of SFA except for the input matrix.

3. ANALYTICS FRAMEWORK FOR MULTIPLE OSCILLATIONS VIA MDSFA

3.1 The proposed MDSFA

A new variant of SFA is presented here. First, the motivation of MDSFA is discussed. By in-depth analysis of the goal of SFA, we can find that the goal of SFA is equivalent to extract features that maximize the one-lag autocorrelation,

$$\begin{aligned}\left\langle \dot{\mathbf{s}}_j^2\right\rangle_t&=\left\langle\left(\mathbf{s}_j(t+1)-\mathbf{s}_j(t)\right)^2\right\rangle_t\\&=\left\langle \mathbf{s}_j(t+1)\mathbf{s}_j(t+1)\right\rangle_t+\left\langle \mathbf{s}_j(t)\mathbf{s}_j(t)\right\rangle_t\\&\quad-\left\langle \mathbf{s}_j(t)\mathbf{s}_j(t+1)\right\rangle_t-\left\langle \mathbf{s}_j(t+1)\mathbf{s}_j(t)\right\rangle_t\\&=2-2\left\langle \mathbf{s}_j(t)\mathbf{s}_j(t+1)\right\rangle_t\\&=2-2R_j(1)\end{aligned} \tag{9}$$

where the one-lag autocorrelation of $\mathbf{s}_j$ is defined as $R_j(1)$ in (10), and $R_j(1)\in[-1,1]$. Due to the zero mean and unit variance of the SF, the calculation can be further simplified as follows.

$$\begin{aligned}R_j(1)&=\frac{\sum_{t=1}^{N-1}\left(\mathbf{s}_j(t)-\overline{\mathbf{s}}_j\right)\left(\mathbf{s}_j(t+1)-\overline{\mathbf{s}}_j\right)}{\sum_{t=1}^{N}\left(\mathbf{s}_j(t)-\overline{\mathbf{s}}_j\right)^2}\\&=\left\langle \mathbf{s}_j(t)\mathbf{s}_j(t+1)\right\rangle_t\end{aligned} \tag{10}$$

It can be simply understood that the slower the signal varies over time, the closer the value of $R_j(1)$ would be to +1.

However, one-lag autocorrelation is only a specific case of the multi-lag autocorrelations. The multi-lag autocorrelations of the output often determine the potential of a controller, which is closely related to the control performance (Huang et al. 2006). Therefore, autocorrelations over other different time lags with more information need to be explored and analyzed. Since the original SFA has covered the one-lag autocorrelation, it is natural to consider extending the SFA to cover multi-lag autocorrelations.

Besides, the time-delay effect is a typical characteristic of process data from coupled control loops. It means that one variable sampled in the current time may be closely related to another variable sampled in the previous time. The structure of the initial process data does not allow the linear combination of measurements in different time instances. However, including the measurements of a past time to construct an augmented matrix $\bar{\mathbf{X}}$ is helpful to eliminate the influence of the time-delay effect.

Motivated by the above analysis, MDSFA is proposed to consider the time-delay effect and multi-lag autocorrelations concurrently. First, the modified optimization function can be constructed as in (11),

$$\min \sum_{k=1}^{K} \left\langle \dot{\mathbf{s}}_{k,j}{}^2 \right\rangle_t \tag{11}$$

where the subscript k denotes the lag of temporal derivatives, and K is often set to be relatively small. This optimization function can be interpreted as to find a map that maximizes the sum of autocorrelations of the SFs over different time lags. The solutions of MDSFA are summarized here.

Step 1: Construct the augmented data matrix as in (8). Normalize the data to have zero mean and unit variance and denote the normalized data as $\mathbf{X}$.

Step 2: Conduct sphering on the process data to eliminate the cross-correlations between variables by applying singular value decomposition (SVD) as in (12). Obtain the sphered matrix $\mathbf{Z}$ by (13).

$$\left\langle \bar{\mathbf{X}}\bar{\mathbf{X}}^{\mathrm{T}} \right\rangle_t = \mathbf{U}\mathbf{\Lambda}\mathbf{U}^{\mathrm{T}} \tag{12}$$

$$\mathbf{Z} = \mathbf{\Lambda}^{-1/2}\mathbf{U}^{\mathrm{T}}\mathbf{X} \tag{13}$$

Step 3: Calculate the k-lag temporal derivative of each vector $\mathbf{z}_j$ in sphered matrix $\mathbf{Z}$ as in (14), assuming the time interval is small. Obtain the transform matrix $\mathbf{W}$ as in (15) and (16).

$$\dot{\mathbf{z}}_{k,j}(t) \approx \frac{\mathbf{z}_j(t) - \mathbf{z}_j(t-k)}{k} \tag{14}$$

$$\sum_{k=1}^{K} \left\langle \dot{\mathbf{Z}}_k \dot{\mathbf{Z}}_k{}^{\mathrm{T}} \right\rangle_t = \mathbf{P}^{\mathrm{T}}\mathbf{\Omega}\mathbf{P} \tag{15}$$

$$\mathbf{W} = \mathbf{P}\mathbf{\Lambda}^{-1/2}\mathbf{U}^{\mathrm{T}} \tag{16}$$

Step 4: Extract features by using (7).

It should be noted that the matrix $\mathbf{P}$ must be an orthogonal matrix, whose elements are orthogonal eigenvectors $\left\{\mathbf{p}_j\right\}_{j=1}^{M}$, and $\mathbf{\Omega}$ is a diagonal matrix with eigenvalues $\left\{\omega_j\right\}_{j=1}^{M}$ arranged in the ascending order. The following relationships can be verified.

$$\left\langle \mathbf{s}\mathbf{s}^{\mathrm{T}} \right\rangle_t = \mathbf{P}\left\langle \mathbf{z}\mathbf{z}^{\mathrm{T}} \right\rangle_t \mathbf{P}^{\mathrm{T}} = \mathbf{I} \tag{17}$$

$$\left\langle \dot{\mathbf{s}}_j{}^2 \right\rangle_t = \mathbf{p}_j{}^{\mathrm{T}} \left\langle \dot{\mathbf{z}}\dot{\mathbf{z}}^{\mathrm{T}} \right\rangle_t \mathbf{p}_j = \omega_j \tag{18}$$

3.2 Detecting and extracting oscillations via MDSFA

Oscillation is a common problem as it harms to the product quality and process safety. Since oscillations often reproduce wave patterns periodically, leading to large autocorrelations over several time lags, oscillations hidden in the data can be revealed in the form of SFs. Moreover, oscillations with different frequencies can be extracted and ranked from the slowest to the fastest by SFA.

Considering that M control loops are designed in the system, M-dimensional measurements of setpoint (SP) and process variable (PV) can be collected at time t in (19) and (20).

$$\mathbf{SP}(t) = \left[sp_1(t), sp_2(t), \ldots, sp_M(t)\right] \tag{19}$$

$$\mathbf{PV}(t) = \left[pv_1(t), pv_2(t), \ldots, pv_M(t)\right] \tag{20}$$

To remove the influence of varying setpoints, the difference between SP and PV is used here to construct the input matrix as in (21).

$$\mathbf{x}(t) = \left[sp_1(t) - pv_1(t), sp_2(t) - pv_2(t), \ldots, sp_M(t) - pv_M(t)\right] \tag{21}$$

By using MDSFA, we can obtain the feature matrix, in which the first J features are selected as SFs and denoted as $\mathbf{s}_j\ (j = 1, 2, \ldots, J)$. After that, the ACF of each SF is obtained by (22) and depicted in Fig. 1.

$$R_j(k) = \frac{\sum_{t=1}^{N-k}\left(\mathbf{s}_j(t) - \bar{\mathbf{s}}_j\right)\left(\mathbf{s}_j(t+k) - \bar{\mathbf{s}}_j\right)}{\sum_{t=1}^{N}\left(\mathbf{s}_j(t) - \bar{\mathbf{s}}_j\right)^2}, j = 1, 2, \ldots, J \tag{22}$$

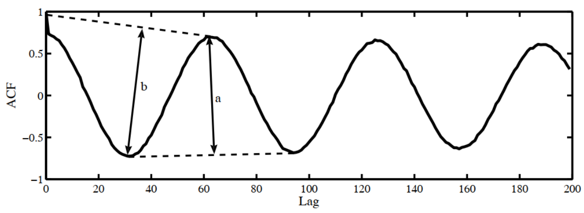

Fig. 1. ACF: Plot of ACF of an oscillatory signal.

To detect the appearance of oscillations, the curve shown in Fig. 1 is used to calculate the oscillation index R_{acf} by (23),

$$R_{acf} = \frac{a}{b} \tag{23}$$

where a is the distance from the first peak to the straight line connecting the first two minima, and b is the distance from the first minimum to the straight line connecting the zero-lag auto-covariance coefficient and the first peak. If the index is greater than the threshold, the SF is oscillatory. Usually, the threshold is set to be 0.5 (Miao et al. 1999). However, it can be adjusted depending on the practical process.

In general, there may be some redundant oscillatory SFs, that is, SFs with the same period, because of the time-embedding. With the increase of lagged measurements, the occurrence of redundancy will increase as more overlapping information is covered. However, as more lagged measurements are added, the extracted SFs would be more similar to the real oscillations, enabling more precise isolation. Hence, the determination of d is a trade-off between the redundancy and accuracy. However, a large d is recommended here since redundant SFs can be removed by using the cyclic cross-correlation analysis to pick out redundant SFs with the same period. After that, the feature with a larger value of R_{acf} is chosen as an oscillation source, while other similar SFs are removed. H oscillation sources can be extracted and denoted as $\mathbf{y}_h (h = 1, 2, \ldots H)$ for further analysis.

3.3 Localization of oscillations via OMD

The basic idea of localization of oscillations is that as the oscillatory signal travels outward, the energy of the signal would decrease gradually due to the attenuation of processes without external power. Hence, the root loop often has the largest energy at the dominant frequency (Naghoosi et al. 2014). Based on it, a novel OMD indicator is proposed here.

To achieve the goal, H oscillation sources are reconstructed by the data from each control loop (Gao et al. 2015). The reconstructed features of M control loops for $\mathbf{y}_h$ can be calculated by projecting $\mathbf{y}_h$ into the subspace spanned by the augmented data of each control loop and denoted as $\hat{\mathbf{y}}_{h,m} \left(m = 1, 2, \ldots, M \right)$. To avoid the matrix irreversibility, least square (Aldrich et al. 1998) based reconstruction is recommended and utilized here as in (24).

$$\hat{\mathbf{y}}_{h,m} = \overline{\mathbf{X}}_m \left(\overline{\mathbf{X}}_m{}^{\mathrm{T}} \overline{\mathbf{X}}_m \right)^{-1} \overline{\mathbf{X}}_m{}^{\mathrm{T}} \mathbf{y}_h \tag{24}$$

Considering that the spectrogram can reveal the spectral information, the spectral analysis is employed to obtain frequencies and amplitudes of a signal. The power spectrum of an oscillation is characterized by a peak at the dominant frequency with much larger power compared to other frequencies. Hence the oscillatory frequency of $\mathbf{y}_h$, termed f_h, can be measured by finding the peak in the power spectrum. By transforming $\hat{\mathbf{y}}_{h,m}$ into the frequency-domain, the amplitudes at different frequencies can be collected. To quantitatively describe the energy of oscillation in the different control loops, the OMD index is designed as in (24).

$$OMD\left(h, m\right) = \frac{a\left(f_h, m\right)}{\sum_{m=1}^{M} a\left(f_h, m\right)} \tag{25}$$

In (24), $a\left(f_h, m\right)$ denotes the amplitude at f_h for $\hat{\mathbf{y}}_{h,m}$, and $m = 1, 2, \ldots, M$. To ascertain the root loop, M scalars can be obtained for each oscillation with f_h. The criterion is that the loop with the largest $OMD\left(h, m\right)$ is judged as the root cause. Besides, the travel path can be found out according to the decreasing direction of the OMD index.

3.4 Framework of analytics for multiple oscillations

For detection problem, possible oscillations can be detected and extracted to constitute the set of oscillation sources based on the proposed MDSFA. For the localization problem, the time-frequency analysis is employed to reveal the root loops and travel paths. The completed procedures of the analytics for multiple oscillations are summarized as follows.

Step 1: Use SP and PV to form the input matrix. Extend the matrix with d lagged time-embedding. Normalize the input matrix to have zero mean and unit variance to obtain $\overline{\mathbf{X}}$.

Step 2: Perform MDSFA on $\overline{\mathbf{X}}$ to obtain J SFs. Calculate the ACF-based index for SFs to detect oscillations. Use cyclic cross-correlation analysis to determine H oscillation sources.

Step 3: Reconstruct each oscillation source in the subspace spanned by each variable and its lagged measurements.

Step 4: Use spectral analysis to determine the oscillatory frequencies of H oscillation sources and the amplitudes at the f_h of reconstructed features to calculate the OMD indicator.

Step 5: Locate the root loop of each oscillation source by finding the largest value of OMD. Make sure the travel paths according to the decreasing direction of the OMD indicator.

4. CASE STUDY

A complex industrial process of the thermal power plant is adopted to verify the performance of the proposed method. The thermal power plants use coal as primary energy and heat the steam by the boiler to drive the turbo-generator to generate electricity (Hu et al. 2020).

The data used in this work are collected from one power plant of Zhejiang Energy Group. In this case, the fan system is chosen as the object, which involves induced draft fan loop (loop 1), blower loop (loop 2), and primary fan loop (loop 3). Hence, M is set as three. Two oscillations are contained in the fan system, one originates from the loop 3 without propagation while the other is also generated in the loop 3 and travels to loop 1.

A data set with 3000 samples are collected. The deviations of SP and PV are used as input variables. By using the MDSFA, eight SFs are extracted as in Fig. 2, indicating that SFs extracted by MDSFA can reveal two oscillation sources. To compare the performance of SFA and MDSFA, three features extracted by SFA are also shown in Fig. 3. It can be seen that SFs in Fig. 3 are still corrupted by other signals without clear periodic patterns. The above comparison implies that the time-embedding and multi-lag temporal derivatives are useful and important. The further analysis of SFs extracted by SFA is omitted for the bad performance in extraction.

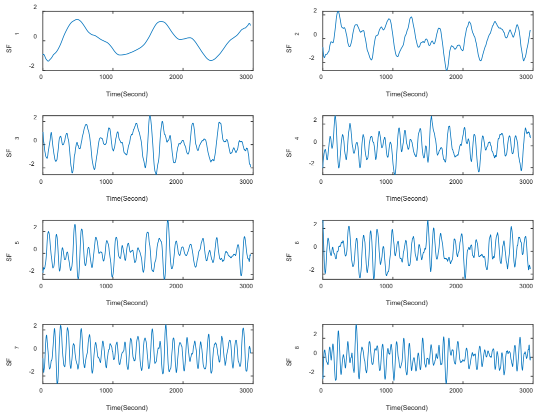

Fig. 2. Eight SFs: Plot of eight SFs extracted by MDSFA.

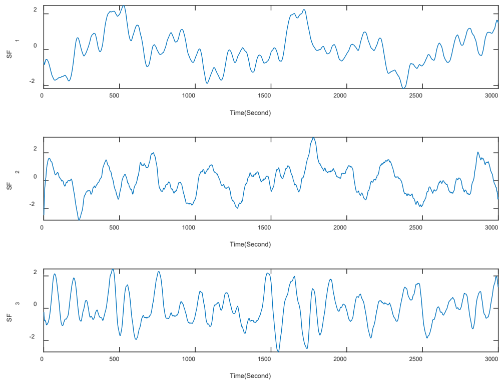

Fig. 3. Three SFs: Plot of three SFs extracted by SFA.

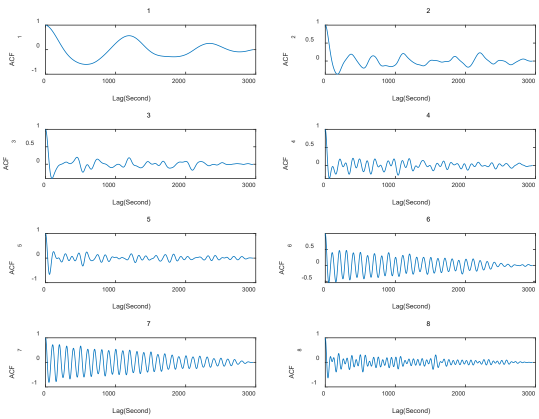

Fig. 4. ACF: Plot of ACFs of eight SFs extracted by MDSFA.

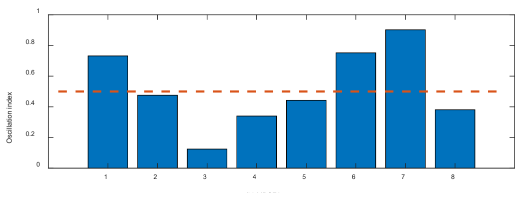

Fig. 5. Oscillation index: Plot of oscillation index for eight SFs by MDSFA.

The ACFs of eight SFs are shown in Fig. 4 whereas the results of R_{acf} are shown in Fig. 5. In Fig. 5, three SFs are tested to be oscillatory with the threshold of 0.5. Besides, SF6 and SF7 are similar to each other via the cyclic cross-correlation analysis. Since the oscillation index of SF7 is larger than that of SF6, SF1 and SF7 are finally chosen as oscillation sources for the further analysis.

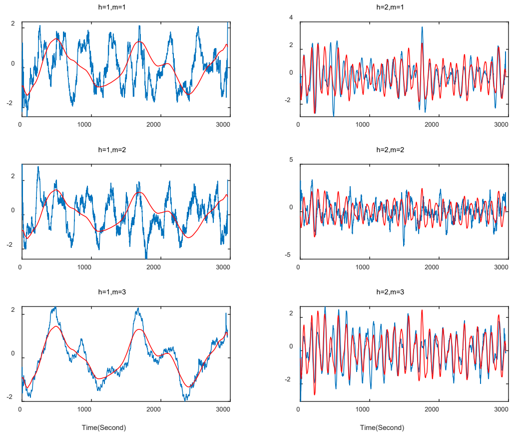

Fig. 6. Reconstruction: Plot of reconstructed features (blue line) and oscillation sources (red line).

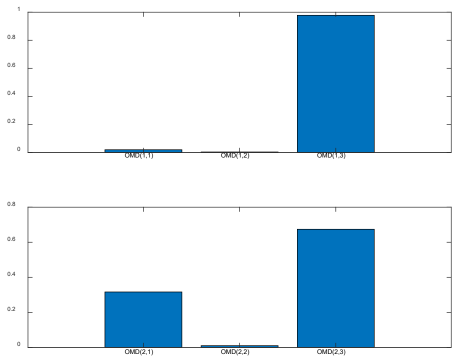

Fig. 7. OMD index: Plot of OMD index for two oscillations.

After the extraction of two oscillation sources, we aim to localize the root loops for isolations. Three reconstructed features for each oscillation source are obtained by (24), shown in Fig. 6. By transforming these signals into frequency-domain, the frequencies and amplitudes can be collected, and the OMD index is calculated as in Fig. 7.

The propagation can be inferred according to the value of OMD: As for the first oscillation, the OMD index of loop 3 is the largest, reflecting that the oscillation starts from loop 3. The OMD index of loop 1 and loop 2 are near to zero, indicating that the oscillation does not travel to loop 1 and loop 2. For the second oscillation, the OMD index of loop 3 is the largest, showing that the root cause is loop 3. The OMD index of loop 1 is a little bit smaller, and the value of loop 2 is almost zero, indicating that the oscillation travels from loop 3 to loop 1, while loop 2 is not influenced. The results of two oscillations are consistent with the facts, hence the proposed method is verified to be effective and applicable.

5. CONCLUSION

In the present work, a new variant of SFA, termed MDSFA, is proposed to consider the time-delay effect and multi-lag temporal derivatives when extracting SFs. Besides, the MDSFA based automatic analytics framework is developed for multiple oscillations in coupled control loops. The proposed method can not only detect and extract the oscillations, but also pinpoint the root loops and travel paths of oscillations using the OMD index based on the feature reconstructions and frequency-domain analysis. The feasibility and efficacy of the proposed method have been evaluated in the real industrial process.

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REFERENCES

Nussbaumer, H.J. (1981). Fast Fourier transform and convolution algorithms. Springer, Berlin.

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

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

Miao, T. and Seborg, D.E. (1999). Automatic detection of excessively oscillatory feedback control loops. IEEE International Conference on Control Applications. 359–364.

Berkes, P. and Wiskott, L. (2005). Slow feature analysis yields a rich repertoire of complex cell properties. Journal of Vision, 5(6): 579-602.

McNabb, C.A. and Qin, S.J. (2005). Fault diagnosis in the feedback-invariant subspace of closed-loop systems. Industrial & Engineering Chemistry Research, 44(8): 2359-2368.

Xia, C., Howell, J. and Thornhill, N.F. (2005). Detecting and isolating multiple plant-wide oscillations via spectral independent component analysis. Automatica, 41(12): 2067-2075.

Huang, B., Ding, S.X. and Thornhill, N. (2006). Alternative solutions to multi-variate control performance assessment problems. Journal of Process Control, 16(5): 457-471.

Jiang, H., Shoukat Choudhury, M.A.A. and Shah, S.L. (2007). Detection and diagnosis of plant-wide oscillations from industrial data using the spectral envelope method. Journal of Process Control, 17(2): 143-155.

Jelali, M. and Huang, B. (2009). Detection and diagnosis of stiction in control loops: State of the art and advanced methods. Springer, London.

Zabiri, H., Maulud, A. and Omar, N. (2009). NN-based algorithm for control valve stiction quantification. WSEAS Transactions on Systems and Control, 4(2): 88-97.

El-Ferik, S., Shareef, M.N. and Ettaleb, L. (2012). Detection and diagnosis of plant-wide oscillations using GA based factorization. Journal of Process Control, 22(1): 321-329.

Naghoosi, E., Huang, B. (2014). Automatic detection and frequency estimation of oscillatory variables in the presence of multiple oscillations. Industrial and Engineering Chemistry Research, 53(22): 9427–9438.

Xu, S., Baldea, M., Edgar, T.F., Wojsznis, W., Blevins, T. and Nixon, M. (2016). Root cause diagnosis of plant-wide oscillations based on information transfer in the frequency domain. Industrial & Engineering Chemistry Research, 55(6): 1623-1629.

Naghoosi, E. and Huang, B. (2017). Wavelet transform based methodology for detection and characterization of multiple oscillations in nonstationary variables. Industrial & Engineering Chemistry Research, 56(8): 2083-2093.

Aftab, M.F., Hovd, M. and Sivalingam, S. (2018). Plant-wide oscillation detection using multivariate empirical mode decomposition. Computers and Chemical Engineering, 117: 320-330.

Yu, W.K. and Zhao, C.H. (2018). Recursive exponential slow feature analysis for fine-scale adaptive processes monitoring with comprehensive operation status identification. IEEE Transactions on Industrial Informatics, 15(6): 3311-3323.

Zhao, C.H. and Huang B. (2018). A full condition monitoring method for nonstationary dynamic chemical processes with cointegration and slow feature analysis. AIChE Journal, 64(5): 1662-1681.

Dambros, J.W.V., Farenzena, M. and Trierweiler, J.O. (2019). Oscillation detection and diagnosis in process industries by pattern recognition technique. IFAC PapersOnLine, 52(1): 299-304.

Dambros, J.W.V., Trierweiler, J.O. and Farenzena, M. (2019). Oscillation detection in process industries-Part I: Review of the detection methods. Journal of Process Control, 78: 108-123.

Dambros, J., Trierweiler, J., Farenzena, M. and Kloft, M. (2019). Oscillation detection in process industries by a machine learning-based approach. Industrial & Engineering Chemistry Research, 58(31): 14180-14192.

Zhang, S.M. and Zhao, C.H. (2019). Slow-feature-analysis-based batch process monitoring with comprehensive interpretation of operation condition deviation and dynamic anomaly. IEEE Transactions on Industrial Electronics, 66(5): 3773-3783.

Zheng, J.L. and Zhao, C.H. (2019). Online monitoring of performance variations and process dynamic anomalies with performance-relevant full decomposition of slow feature analysis. Journal of Process Control, 80: 89-102.

Hu, Y.Y. and Zhao, C.H. (2020). Fault Diagnosis with Dual Cointegration Analysis of Common and Specific Nonstationary Fault Variations. IEEE Transactions on Automation Science and Engineering, 17(1): 237–247.