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Data-driven root-cause fault diagnosis for multivariate non-linear processes

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A B S T R A C T

In a majority of multivariate processes, propagating nature of malfunctions makes the fault diagnosis a challenging task. This paper presents a novel data-driven strategy for real-time root-cause fault diagnosis in multivariate (non-)linear processes by estimating the strength of causality using normalized transfer entropy (NTE) between measured process variables and variations of a residual signal. In this paper, a new framework for root-cause fault diagnosis applicable for multivariate nonlinear processes is proposed, which can reduce the necessary number of calculation for causality analysis among time-series. More specially, a new and fast symbolic dynamic-based normalized transfer entropy (SDNTE) technique is proposed to enable real-time application of transfer entropy, which has been considered as a burdensome approach for causality analysis. The concept of SDNTE is built upon principles of time-series symbolization, xD-Markov machine and Shannon entropy. This paper also introduces a new concept of joint xD-Markov machine to capture dynamic interactions between two time-series. The proposed root-cause fault diagnosis framework is applied on Tennessee Eastman process benchmark and its computational advantages are shown by comparing with conventional kernel PDF-based method. Moreover, the proposed strategy is applied to health monitoring of a big scale industry centrifuge to corroborates its effectiveness and feasibility in industrial applications.

1. Introduction

Process health monitoring algorithms have been widely used in industrial processes to effectively increase the level of safety and reliability as well as reduce maintenance costs by detecting anomalies that require attention. The issues of fault detection and identification of the faulty variables have been well addressed by numerous model-based and data-driven methods. However, root-cause fault diagnosis of process malfunctions still remains an ongoing challenge. To tackle this issue, a novel data-driven framework for root-cause fault diagnosis applicable to non-linear multivariate industry processes is proposed. The strategy presented in this paper requires no *a priori* knowledge about the governing equations of industry processes, which may be considered as an advantage over model-based approaches. Moreover, in comparison with state-of-the-art methods, the proposed methodology provides a faster alternative, which enables early root-cause fault diagnosis for real-time applications.

The majority of process monitoring techniques may be classified into model-based or data-driven categories. In Hwang et al. (2010), a thorough survey is conducted on various model-based approaches for fault detection-diagnosis. For instance, Li etal. (2017) Youssef et al. (2017) and Chibani et al. (2016) are the recent model-based techniques that consider a T–S fuzzy model for non-linear processes and adopt integrated observers and filters for detection and estimation of process malfunction(s). However, these model-based techniques may not be applicable for a high-dimensional process, specially when the dynamic model of the process is not available. Since this paper is mainly focused on tackling the root-cause fault diagnosis of multivariate non-linear industry processes from a data-driven perspective, the following review is centered on data-driven approaches for root-cause fault diagnosis.

For fault detection and diagnosis purposes, many qualitative and quantitative data-driven methods have been proposed and well summarized in surveys (Venkatasubramanian et al., 2003b; Venkatasubramanian et al., 2003a). In Yin et al. (2012), a survey is conducted on common data-driven fault detection methods, and their important features and limitations are summarized. Among these methods, various modified versions of PCA were utilized for different types of processes (Ku et al., 1995; Scholkopf et al., 1999). For the case of multivariate non-linear industrial processes, kernel PCA is widely used (Lee et al., 2004; Hoffmann, 2007; Cho et al., 2005). Kernel PCA is a modified version of PCA, which, by utilizing *kernel* trick, first maps

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the process variables with non-linear relations onto a high-dimensional feature space and then deploys the standard PCA to generate statistical error indices for process health monitoring. This paper is focused on the root-cause identification of faults in multivariate non-linear processes, thus the proposed method in this paper utilizes the kernel trick for dealing with the non-linearity in the process and calculation of a proper residual for fault detection.

In general, the underlying idea of PCA-based algorithms including kernel PCA is about finding correlation(s) among process variables. Therefore, certain common methods for fault diagnosis, such as contribution plot analysis of PCA and kernel PCA, may suffer from smearing-out effects as a result of fault propagation (Kerkhof et al., 2013; Alcala & Qin, 2009). Consequently, these methods may not be able to locate the root-cause fault in an industrial process. This limitation is due to the lack of considering causal relationships among process variables, which are of great importance for identifying source(s) of the fault. For this purpose, this paper proposes a new root-cause fault diagnosis framework based on finding the causal relations (e.g. strength of information flows) from process variables to a residual signal generated by the kernel PCA method.

Time-series (i.e. process variables and residual(s)) can be classified into two categories, the (quasi-)stationary and non-stationary ones. There already exist several methods for causality analysis of the stationary/quasi-stationary time-series including spectral envelope, adjacency matrix, Bayesian network interface, Granger causality (GC) and transfer entropy (TE). For the non-stationary cases, application of the aforementioned methods might lead to erroneous result, thus other alternatives such as dynamic time warping (DTW) analysis (Li et al., 2016a) can be applied to identify the root-cause of malfunction.

For the problem of root-cause diagnosis, Duan et al. reviewed several methods in Duan et al. (2014) for the issue of plant-wide oscillation (Thornhill et al., 2003; Thornhill & Hägglund, 1997), which meets the criterion of a quasi-stationary process. Among those methods, spectral envelope is presented as a causality analysis scheme in frequency domain (Jiang et al., 2007). A graph-based method so called adjacency matrix (Jiang et al., 2009) is another technique strictly dependent on process model, which is not always available specially for the industrial cases. Bayesian network (BN) interface (Weidl et al., 2005), as a direct acyclic graph method, is applicable to cases where less amount of historical data is available. BN method suffers from high computational complexity as well as several limiting assumptions for industrial applications. Granger causality (GC) is another common scheme that finds the causal relations among time-series utilizing the ARMA structure. This method is easy to implement and has low computational complexity, but it is not applicable to the case of time-series with non-linear relationship (Yuan & Qin, 2014; Li et al., 2016b).

Transfer entropy (TE) which was first proposed in Schreibers (2000) is another conventional and viable tool for finding causality between two time-series. TE has been widely adopted in different industrial and neuroscience applications. In Bauer, Cox, Caveness, Downs, and Thornhill (2007) Landman & Jämsä-Jounela (2016), TE is applied to find cause and effect relations (causal map) among process variables in a multivariate industry process. Moreover, Le et al. utilized TE to find the root-cause of fault among the suspicious candidates chosen from all process variables by utilizing reconstruction-based contribution method. There exist different versions of transfer entropy, such as so called direct transfer entropy (DTE) (Duan, Yang, Chen, & Shah, 2013) and transfer zero entropy (Duan, Yang, Shah, & Chen, 2015), which provide more explicit information about the existing direct pathways between time-series.

The key-point about the TE approach for causality analysis is that it relies on the distribution (i.e. joint probability density functions) of the process variables rather than their regression model, which is the case in Granger causality. Hence, TE can be applied to both linear and non-linear processes (Duan et al., 2013). This advantage of the TE over GC motivates authors to utilize transfer entropy for root-cause diagnosis. On the other hand, as mentioned in Li et al. (2016a) Bauer et al. (2007) Duan et al. (2013), causality analysis using TE requires a burdensome computational effort and may not be applicable for real-time root-cause diagnosis. The reason behind this computational obstacle is that in almost all of the proposed TE-based methods, joint probability density functions (PDFs) in definition of TE are estimated by kernel functions (Silverman, 1986), which has high computational order and requires significant amount of temporal data. Therefore, this computational complexity limits application of TE-based methods to off-line causality analysis in industrial processes. In order to address this limiting disadvantage of the TE method, authors propose a new and fast *symbolic dynamic-based* pathway for estimating transfer entropy of time-series, which has significantly lower computational order in calculating transfer entropy in comparison with conventional kernel-based methods. The proposed symbolic dynamic-based normalized transfer entropy (SDNTE) method also requires less amount of historical process data to reveal causality between two time-series, enabling early fault diagnosis and real-time application of transfer entropy. For completeness, symbolic dynamic filtering (SDF) method is introduced and its literature is reviewed in Section 3.2.

The schematic diagram that summarizes the main steps of the proposed strategy is shown in Fig. 1. In the first part, a reduced-rank kernel trick introduced in Kwak (2013) is applied to project the process variables $\mathbf{X} \in \mathcal{R}^{N\times m}$ with non-linear relations onto a higher dimensional linear space $\mathbf{\Phi}(X) \in \mathcal{R}^{f\times N}$. Then, a residual index used as a fault indicator is calculated. In the next step, a stationary test (e.g. Li, Qin, and Yuan, 2014) is conducted on the residual signal to switch between the proposed SDNTE strategy and an alternative method applicable for non-stationary faults such as, dynamic time warping (DTW) (Li et al., 2016a). In the second phase (root-cause diagnosis mechanism in Fig. 1), for the case of (quasi-)stationary faults, it is proposed to find strength of causality, which is measured by the proposed symbolic dynamic-based normalized transfer entropy (SDNTE) from each process variable $x \in \mathbf{X}$ to the residual signal ψ. The underlying idea behind the proposed framework is that the source of fault has stronger causal contribution on the residual signal, while in the normal (i.e. fault free) situation, there is no significant causal pathway between process variables and the residual signal. It should be noted that the relationship between the generated residual signal ψ and process variables $\mathbf{X}$ are mainly non-linear, thus, normalized transfer entropy (NTE) that is applicable to non-linear relations is defined and utilized for causality analysis.

In brief, the main contributions of this paper are listed as follows,

1—A novel data-driven framework is proposed to locate the source of (quasi-)stationary faults in high-dimensional non-linear processes. This strategy utilizes normalized transfer entropy (NTE) to determine the causality pathways from (m) process variables to a residual signal, which requires less number of NTE calculation (i.e. m times) in comparison with other existing methods (e.g. Li et al., 2016a; Hajihosseini, Salahshoor, & Moshiri, 2014) that require to calculate transfer entropy $m(m-1)$ times (i.e. total number of possible causality pathways among all process variables).

2—A novel and fast technique based on symbolic dynamic modeling of time-series is proposed for calculation of transfer entropy (TE). By utilizing the proposed technique, symbolic dynamic-based normalized transfer entropy (SDNTE) is defined for real-time causality analysis of time-series. This proposed symbolic dynamic-based approach for estimating TE has lower computational order and requires less amount of historical data in comparison with kernel functions utilized for transfer entropy estimation. This contribution enables real-time application of transfer entropy (TE) for early root-cause fault diagnosis in industrial processes.

3—The proposed framework and SDNTE technique are applied to an industrial centrifuge for the first time, which corroborates its feasibility and effectiveness for industrial applications.

The rest of the paper is organized as follows: in Section 2, the preliminaries for residual generation using kernel trick are briefly