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Dominant trend based logistic regression for fault diagnosis in nonstationary processes

Jun Shang [a], Maoyin Chen [a], Hongquan Ji [a], Donghua Zhou [b,a,*], Haifeng Zhang [c], Mingliang Li [c]

[a] Department of Automation, TNList, Tsinghua University, Beijing 100084, China
[b] College of Electrical Engineering and Automation, Shandong University of Science and Technology, Qingdao 266590, China
[c] Guangxi Liuzhou Iron and Steel (Group) Company, Liuzhou 545002, China

A R T I C L E   I N F O

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A B S T R A C T

This paper presents a fault diagnosis method called dominant trend based logistic regression (DTLR) for monitoring nonstationary processes. Different from conventional sample-wise diagnosis approaches, it uses sliding windows to collect process data and extract dominant trend features. After data preprocessing via robust sparse representation, the feature vector reflecting variation trend is obtained by solving a convex optimization problem, i.e., dominant trend extraction (DTE). Then the ℓ_2-norm of the dominant trend vector is used as a detection index to quantify the dissimilarity between normal and abnormal conditions. Once it exceeds the control limit, the feature vector is used to train the weight vector of logistic regression. The fault type can be determined as the class with the maximum conditional probability. With trend information, DTLR can effectively detect and isolate faults in nonstationary processes. Simulations on a synthetic nonstationary dynamic process, a nonstationary continuous stirred tank reactor (CSTR), and the real data of a blast furnace iron-making process illustrate superior monitoring and isolation performance of DTLR, compared with conventional methods.

1. Introduction

For most modern industrial processes, effective monitoring is critically important for process safety and production efficiency (Agrawal, Panigrahi, & Subbarao, 2015; Alcala & Qin, 2011). In the past decades, there have been extensive studies and applications on fault diagnosis techniques, especially multivariate statistical process monitoring (MSPM) (Fan, Qin, & Wang, 2014; Ji, He, Shang, & Zhou, 2016, 2017; Kruger, Zhou, & Irwin, 2004; Qin, 2003, 2012; Tong, Lan, & Shi, 2017; Zhao, Wang, & Zhang, 2009). In general, fault diagnosis mainly includes fault detection and fault isolation (Ding, 2014). The former is to decide whether faults occur or not, and the latter is to determine the fault type after the detection of faults. For data-driven methods, fault detection needs historical data under normal conditions for training, and fault isolation can be divided into two cases, i.e., with or without historical data containing fault. Accordingly, the objective of fault isolation is to determine the exact fault type, or to find the most responsible variable for the fault.

In practical industrial processes, the operating conditions usually exhibit time-varying statistical properties due to slow process changes, which may be caused by catalyst deactivation, equipment aging, sensor drifting, or preventive maintenance (Li, Yue, Valle-Cervantes, & Qin, 2000). In other words, industrial processes rarely behave in stationary manners if long-time continuous operation is considered (Ketelaere, Mertens, Mathijs, Diaz, & Baerdemaeker, 2011). The nonstationarity frequently occurs at some practical processes, such as blast furnace iron-making processes (Zhou, Ye, Zhang, & Li, 2016), rapid thermal annealing processes (Li et al., 2000), and biological processes (Ketelaere et al., 2011). For these processes, the measured variables are not strictly stationary, and their statistical properties usually exhibit slowly time-varying behaviors. In this circumstance, the fixed-model monitoring approaches such as principal component analysis (PCA) and partial least squares (PLS) may lead to a significant number of false alarms. Hence, these methods may not be applicable to monitor nonstationary processes.

For different types of nonstationary time series, nonstationary behaviors can be attributed to specific deterministic and stochastic trends in the moments (Cheng et al., 2015; Kirchgässner, Wolters, & Hassler, 2013). For instance, for a first-order nonstationary time series, its stationarity is violated since its expectation depends on time. Specifically, the time series may exhibit upward, downward, or cyclic trend

* Corresponding author.
E-mail address: zdh@tsinghua.edu.cn (D. Zhou).

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(Cheng et al., 2015). The trend can be stochastic such as the first-order random walk, which can be modeled by autoregressive integrated moving average (ARIMA) (Berthouex & Box, 1996). For processes with time-varying first-order moments, De Oca, Jeske, Zhang, Rendon, and Marvasti (2010) adapted the CUSUM change-point detection algorithm to cope with nonstationary sequences. Wang, Bukkapatnam, Kumara, Kong, and Katz (2014) presented a Dirichlet process Gaussian state machine representation to capture complex dynamics as a random concatenation of nonlinear stationary segments, in order to detect early-stage fault-inducing changes. This method was successfully applied in an ultraprecision machining process and a chemical mechanical planarization process. For processes with time-varying secondary moments, Choi, Ombao, and Ray (2008) proposed two spectral methods for detecting changes in autocorrelation structure in continuous-valued time series.

Another important tool in nonstationary time series is cointegration test, which analyzes the relations between the nonstationary variables sharing common trends. Xu and Chen (2007) introduced cointegration test method for nonstationary system monitoring and fault diagnosis, which was successfully applied in a simulated nonstationary fluid catalytic cracking unit. Chen, Kruger, and Leung (2009) designed a cointegration test based method for monitoring nonstationary processes. In this approach, a cointegration model of the tested nonstationary variables is identified, whose residual sequence describes the dynamic equilibrium errors of the nonstationary process, which can be utilized for fault detection. For structural health monitoring data, Cross, Worden, and Chen (2011) utilized cointegration to deal with the problem of environmental variation in monitored features. Besides, Dao and Staszewski (2013) utilized cointegration to remove the undesired temperature effect from Lamb wave data. Li, Qin, and Yuan (2014) used cointegration tests for monitoring nonstationary dynamic processes, with application to the Tennessee Eastman process. Shi, Chen, and Lin (2015) proposed a fault diagnosis method based on cointegration coefficients matrix. Its elements are stacked into feature vectors, which are used for training support vector machine (SVM) for classification.

Apart from the above methods based on time series analysis, many recursive or adaptive MSPM methods have been extensively discussed, which are also used for monitoring nonstationary processes. Li et al. (2000) proposed two recursive PCA algorithms based on rank-one modification and Lanczos tridiagonalization for coping with normal process changes. Elshenawy, Yin, Naik, and Ding (2009) developed another two recursive PCA algorithms based on first-order perturbation (FOP) analysis and data projection method. All of these tricks are aimed at reducing the computational cost. Wang, Kruger, and Irwin (2005) proposed a fast moving window PCA with the introduction of an N-step-ahead horizon. Jin, Lee, Lee, and Han (2006) developed a robust recursive PCA approach for adaptive monitoring as well as removing disturbances. An adaptive MSPM method with forgetting factors was designed by Choi, Martin, Morris, and Lee (2006) for monitoring processes with operating condition changes. Liu, Kruger, Littler, Xie, and Wang (2009) proposed a moving window kernel PCA for monitoring nonlinear and time-varying processes. Ma, Shi, Ma, and Wang (2013) designed a moving window local outlier factor (LOF) algorithm for monitoring processes with time-varying and multimode characteristics. A manifold learning based fault detection method was proposed by Zhang and Zhang (2014) for monitoring time-varying processes. An adaptive modification of total partial least squares (TPLS) (Zhou, Li, & Qin, 2010) model called recursive TPLS was proposed by Dong, Zhang, Huang, Li, and Peng (2015) for adaptive process monitoring. Portnoy, Melendez, Pinzon, and Sanjuan (2016) proposed a weighted adaptive recursive PCA for detecting faults in processes with slow but normal changes. A nonparametric control chart was presented by Kang, Yu, and Kim (2016) for adaptively monitoring time-varying and multimodal processes. Gao, Wang, Wang, and Zhao (2016) developed an incremental PCA for detecting slow ramp faults in time-varying chemical processes. Khediri, Limam, and Weihs (2011) proposed a variable window monitoring approach based on fast block adaptive kernel PCA.

Compared with the problem of fault detection, the issue of fault isolation in nonstationary processes is less discussed. Note that the classic contribution analysis methods such as reconstruction-based contribution (RBC) (Alcala & Qin, 2009; Ji, He, & Zhou, 2016; Yue & Qin, 2001) are more suitable for sensor faults owing to their mechanisms. However, due to the time-varying nature of the measured variables, they may be unsuitable for nonstationary processes. Accordingly, Elshenawy and Awad (2012) proposed two methods, i.e., recursive partial decomposition contribution (RPDC) and recursive diagonal contribution (RDC), for isolating faults in time-varying processes without historical faulty data. However, if the historical data containing information of typical faults exist, they may be useful for fault diagnosis. So far, little has been reported on the development of general fault isolation with labeled training data containing faults. Ni, Zhang, and Yang (2011) proposed a fault diagnosis method based on adaptive kernel PCA and SVM for monitoring high-voltage circuit breakers. Liu and Chen (2009) proposed a modified Bayesian classification on PCA subspace. In fact, if some historical faulty data are available, one simple idea is to utilize the classic machine learning methods such as SVM (Jing & Hua, 2008; Liu, He, & Zhang, 2008; Widodo & Yang, 2007) and Fisher discriminant analysis (FDA) (Chiang, Kotanchek, & Kordon, 2004; Chiang, Russell, & Braatz, 2000; He, Qin, & Wang, 2005) to diagnose faults. These approaches are considered to be applicable for stationary processes. However, in nonstationary processes, faults occurring at different temporal intervals may have different statistical properties. In other words, there may exist obvious dissimilarities in different time intervals. Besides, faulty data usually own time-varying behaviors, which increases the difficulty to correctly diagnose the faults. In the literature, most existing isolation or classification methods utilize single faulty sample each time, which may weaken their diagnosability.

In this paper, we propose a new fault diagnosis method called dominant trend based logistic regression (DTLR). Different from conventional sample-wise fault diagnosis methods, we use sliding windows to collect process data and extract dominant trend features. This process can be obtained from a convex optimization problem, which can be effectively solved by alternating direction method of multipliers (ADMM) (Boyd, Parikh, Chu, Peleato, & Eckstein, 2011). After dominant trend extraction (DTE), the ℓ_2-norm of the feature vector is selected as the detection index. The feature vector with the detection index exceeding the control limit is used to train the weight vector of logistic regression. The fault type is then determined through conditional probability. Compared with conventional sample-wise fault diagnosis methods, DTLR utilizes the information on variation trend of the measurements, which can be useful for distinguishing normal and abnormal conditions, and different types of faults.

The remainder of this paper is organized as follows. Preliminaries and problem formulation are given in Section 2. The main content of DTLR is elaborated in Section 3, including data preprocessing, dominant trend extraction, dissimilarity quantification, and multinomial logistic regression. The entire fault diagnosis procedure is summarized in Section 3.5. In Section 4, simulations on a synthetic nonstationary dynamic process with PI controller, a nonstationary continuous stirred tank reactor (CSTR), and a blast furnace iron-making process are used to verify the effectiveness of DTLR. Conclusions are given in Section 5.

2. Preliminaries and problem formulation

Consider an industrial process with m measured variables $\boldsymbol{x}_1, \ldots, \boldsymbol{x}_m$. The process is uniformly periodically sampled, namely, the sampling interval is constant. Assume the probability distribution functions of some measured variables are slowly time-varying, and a certain amount of historical data are recorded. Denote $\boldsymbol{X}^{[0]} \in \mathbb{R}^{m\times n}$ as the historical dataset under normal conditions. This dataset is collected in the single time interval with sufficient n samples. Suppose there exist r types of typical faults. Apart from $\boldsymbol{X}^{[0]}$, there are M historical datasets respectively containing r types of faults, i.e., $\boldsymbol{X}^{[i]} \in \mathbb{R}^{m\times n_i}$ with label $l_i \in [1, r]$, where $i = 1, \ldots, M$.