Concurrent Monitoring and Diagnosis of Process and Quality Faults with Canonical Correlation Analysis

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Abstract: Partial least squares and canonical correlation analysis are latent variable models suitable for quality-relevant monitoring based on process and quality data. Recently, concurrent monitoring schemes are proposed to achieve simultaneous process and quality monitoring. This paper defines and analyzes quality-relevant monitoring based on these popular latent structure modeling methods, and the associated quality-relevant monitoring statistics are defined. Additionally, contribution plots and reconstruction-based contribution diagnosis methods are developed for concurrent fault diagnosis. Multi-dimensional quality-relevant faults can be diagnosed in the same reconstruction framework. Finally, a detailed case study on Tennessee Eastman process is shown to illustrate the diagnosis of process and quality faults and the prognosis of quality-relevant faults.

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Keywords: Quality-Relevant Diagnosis, Reconstruction-based Contribution, Contribution Plots, Canonical Correlation Analysis, Quality-Relevant Fault Prognosis

1. INTRODUCTION

Statistical process monitoring and fault diagnosis apply multivariate statistical analysis techniques on a large amount of process data to monitor and diagnose disturbances in a process, which has been one of the most active research areas in process control over the past several decades (Qin (2003, 2012)). However, in practice, anomalies detected by process variables alone may not lead to an anomaly in product quality due to corrective effort by human operators and feedback controllers. The quality-relevant variations should receive a higher level of attention than process-relevant variations. Alarming on faults due to process variable deviations alone may lead to nuisance alarms and reduce the reliability of the fault detection methods. Thus, quality-relevant monitoring and diagnosis will be the focus in this paper.

With the availability of high dimensional process data or big data, data-driven latent structure modeling methods, such as principal component analysis (PCA), partial least squares (PLS) and canonical correlation analysis (CCA), are typical modeling tools for fault detection and diagnosis in industries (Qin (2014); Qin and Zheng (2013); Wise and Gallagher (1996); Zhu et al. (2016)). PLS is a data decomposition method for maximizing covariances between process variables $X$ and quality variables $Y$. With iterative calculations, PLS decomposes the original spaces into principal and residual subspaces, which can be monitored by $T^2$ and $Q$ statistics, respectively. However, PLS usually requires many factors to predict even one output variable, making a large fraction of the latent space orthogonal to the output to be predicted. In addition, PLS can leave large variances in the residual subspace if they are irrelevant to predict the output, which is different from PCA residuals and thus should be monitored differently from PCA based monitoring indices. Recent efforts have been devoted to overcome these issues, including total PLS (Zhou et al. (2010)), concurrent PLS (Qin and Zheng (2013)), and concurrent CCA (Zhu et al. (2016)).

PLS related methods simultaneously exploit the process and quality structures, and are robust to collinearity. CCA, in contrast, extracts the multidimensional correlation between $X$ and $Y$ with no attention to the magnitude of the variance in each set of variables, which enables it to build an efficient model with as few latent factors as possible. In doing so, however, CCA requires to invert the input and output covariance matrices, making it susceptible to collinearity or strong correlations. In this case, regularized CCA is preferred to improve the robustness of the method. Considering the efficiency of CCA over PLS, Zhu et al. (2016) proposed a concurrent CCA (CCCA) algorithm, which decomposes the inputs into quality-relevant and quality-irrelevant spaces, and the corresponding monitoring scheme is also developed.
For multivariate quality-relevant monitoring, after detecting faults, their root causes should also be analyzed. Contribution plots, as an early and popular approach, are employed to diagnose a fault by determining the contribution of each variable to the fault detection indices (Miller et al. (1998); Nomikos and MacGregor (1995)). However, Westerhuis et al. (2000) showed that contribution plots has smearing effects, which can lead to misleading results.

Rigorous diagnosability analysis is available for the reconstruction method (Dunia and Qin (1998)). The advantage of the reconstruction based method is that faults with known fault directions can be diagnosed without ambiguity, but it requires prior knowledge of fault directions. In order to overcome this problem, Alcala and Qin (2009) proposed a reconstruction-based contribution (RBC) method, and defined the amount of reconstruction along each variable direction that minimizes the fault detection index as the RBC of that variable. Alternatively, when fault data are available for a particular fault, the fault direction can be extracted in the residual space or principal component space using singular value decomposition (Qin et al. (2001)). With the knowledge of the fault directions, an extended RBC is suitable for multidimensional fault diagnosis.

The remaining sections of this paper are organized as follows. In Section 2, a description and analysis of quality-relevant monitoring are provided, and several quality-relevant fault detection statistics are analyzed. The traditional contribution plots and RBC diagnosis approaches are defined for CCCA in Section 3. Additionally, an extended RBC method is also proposed to diagnose multidimensional faults. In Section 4, appropriate monitoring schemes of Tennessee Eastman process on quality-relevant monitoring and diagnosis are employed to illustrate the performance of these methods. Finally, conclusions are drawn in the last section.

2. QUALITY-RELEVANT FAULT DETECTION

In this section, several types of fault monitoring schemes are described and analyzed, including process monitoring, quality monitoring, quality-relevant monitoring and quality-irrelevant process monitoring. Quality-relevant monitoring is highlighted as a new scheme, and some of their recent developments are presented.

2.1 Fault Monitoring Schemes

Two different methodologies are available in fault monitoring. One is to build models for the process based on first-principles, and the other is to build a model with normal data and use it to detect faults that deviate from the normal case, which is named as data-driven method. It is obvious that the former approach requires much more modeling effort than the latter one, and it can be difficult to build rigorous models related to various types of quality variables. Thus, the data-driven approach is more popular in industries, with tools ranging from PCA, PLS, CCA, and other variants. Depending on the variations in the process and quality data, monitoring schemes can be classified into four types.

(1) Process monitoring (PM). PM applies multivariate statistics and machine learning methods to fault detection and diagnosis based on process data, and PCA is one of the most popular methods. PM focuses on monitoring variations inside process variables, and no information of the quality variables is included or required. It works well to monitor and diagnose faults in the process; however, the variations or disturbances among process variables may have no influence on the final quality, since they can be compensated by feedback controllers. Thus, monitoring the process variables only can easily lead to nuisance alarms that have no sensible effect on quality variables.

(2) Quality monitoring (QM). Since product quality is the main concern in industries, QM has been practiced which focuses on the variations in quality variables. Typically the Hotelling’s T² and Q statistics are used to detect the abnormal cases in QM (Jackson (1991)). However, it is difficult for QM to pinpoint to which process variables contribute to the quality problems. Additionally, quality variables are usually measured at a much slower rate than process variables with measurement delays, thus a large delay often occurs in QM-based fault detection and diagnosis.

(3) Quality-relevant monitoring (QRM). QRM refers to the fault detection and diagnosis of quality variables that can be inferred or predicted from process variables. Input-output data driven models built from, e.g., PLS and CCA, are usually employed in QRM (Qin and Zheng (2013); Zhou et al. (2010); Zhu et al. (2016)). QRM can have tiers in its structure depend on the use of mid-course, intermediate or final quality variables. For example, the quality variables in Tier 1 can be composed of final or main product quality, and variables in Tier 2 can be composed of intermediate quality variables.

(4) Quality-irrelevant process monitoring (QIPM). As opposed to QRM, process variations that are not quality relevant can also be monitored, although its attention level should be much lower than QRM, since they are excited in the data but have no relevance to quality. The monitoring of this portion of variations is the same as regular PM, only that the portion of quality relevant variations is removed.

In the following sections, QRM will be the main focus, since it can provide monitoring of quality variables with process measurements using an inferential model that can be executed as frequent and as soon as the process measurements are available. In this sense, QRM is prognostic. On the other hand, QM is the final authority to determine whether product quality is indeed abnormal or not, although it usually involves long time delays and long sampling intervals. Since the quality variables cannot be perfectly predicted from process variables, depending on the model goodness of fitting, there can still be false alarms using QRM to predict quality anomalies. Nevertheless, since QRM uses supervised models with the help of quality data in the model building phase, while PM uses unsupervised models, the fault detection rates (FDR) and false alarm rates (FAR) for QRM should be lower than those from PM. The definitions of FDR and FAR are
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