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Diagnosis of multiple and unknown faults using the causal map and multivariate statistics

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ABSTRACT

Feature extraction is crucial for fault diagnosis and the use of complementary features allows for improved diagnostic performance. Most of the existing fault diagnosis methods only utilize data-driven and causal connectivity-based features of faults, whereas the important complementary feature of the propagation paths of faults is not incorporated. The propagation path-based feature is important to represent the intrinsic properties of faults and plays a significant role in fault diagnosis, particularly for the diagnosis of multiple and unknown faults. In this article, a three-step framework based on the modified distance (DI) and modified causal dependency (CD) is proposed to integrate the data-driven and causal connectivity-based features with the propagation path-based feature for diagnosing known, unknown, and multiple faults. The effectiveness of the proposed approach is demonstrated on the Tennessee Eastman process.

1. Introduction

Feature extraction is a process that builds derived values (features) from an initial set of information to inform and facilitate the desired task, in some cases leading to better human interpretations. Feature extraction is crucial for fault diagnosis. Extraction of features that can fully reflect the intrinsic properties of the faults, especially the unknown and multiple faults, is still a challenging problem. This issue has not been extensively explored in fault monitoring, in contrast to the high level of achievement in pattern recognition and image processing [1].

The purpose of fault diagnosis is to determine the root causes of process faults, which facilitates efficient, safe, and optimal operation of industrial processes [2]. The chemical industry mostly constructs process monitoring systems based on process data, and several reviews on fault diagnosis based on data-driven feature extraction are available [3–8]. Those fault diagnosis methods typically do not utilize the preliminary process knowledge. The traditional techniques purely based on historical process data have an inherent limitation for diagnosing multiple faults. Multiple faults can be defined as two or more faults occur simultaneously or sequentially, which can be categorized as being of four types: induced fault, independent multiple faults, masked multiple faults, and dependent faults [9], as shown in Fig. 1. The joint effect on overlapping variables can be very different than the effect of the individual faults. In those data-driven diagnosis techniques, a few variables are isolated as the candidates for the likely root cause of the faults. In large-scale plants with high complexity, it is difficult to conclude whether a certain variable is the root cause by analyzing plant data alone [10,11].

To address this drawback, the feature representation of causal connectivity of the components within the plant is considered and several ways of combining data-driven techniques with cause-and-effect information from a process flow diagram or piping and instrumentation diagram have been carried out. Lee et al. [9] utilized a hybrid method of signed digraph and partial least squares for the fault diagnosis of chemical processes. Using the local qualitative relationships of each variable in a signed digraph, a process is decomposed into subprocesses. A partial least-squares model is then built for the estimation of each measured variable in each decomposed subprocess. Alternately, Thornhill et al. [12] showed

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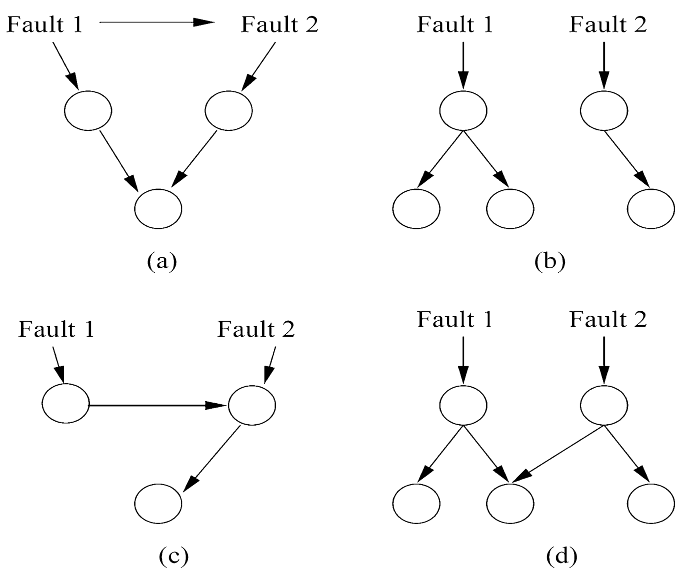

Fig. 1. Four types of multiple faults: (a) induced faults, (b) independent faults, (c) masked multiple faults, and (d) dependent multiple faults. A node represents a symptom and a vector represents the causal relationship between two nodes.

how data-driven methods in combination with cause-and-effect relationships among process variables could lead to efficient root cause diagnosis, where the root cause of a plant-wide oscillatory disturbance was determined, and its means of propagation understood. More recently, Thambirajah et al. [13] also developed an approach that combines the data-driven technique of transfer entropy with a technique that uses the cause-and-effect information in the plant schematic in the form of a connectivity matrix. The core technology for the extraction of a connectivity matrix is an XML code of the chemical plant that represents the items of equipment and the links between them.

Aside from the feature extractions from data-driven and causal map techniques, the propagation path of a fault is another important feature for representing the intrinsic properties of faults. As shown in Fig. 1, different faults often have their own distinctive dynamic propagation among process variables. Such information plays a significant role in fault diagnosis, particularly for the diagnosis of multiple and unknown faults. The feature of fault propagation path is significantly different from the aforementioned two feature representations extracted from plant data and causal connectivity (DI and CD, respectively), and can effectively complement them to allow better diagnostic performance. It was shown in [14] that the information provided by different feature representations can be complementary and the use of complementary features greatly improves diagnosis performance.

This study proposes a scheme that incorporates more complete feature representations for fault diagnosis. Previously, the authors introduced the modified distance (DI) and modified causal dependency (CD) to incorporate the data-driven approach in conjunction with the causal connectivity-based approach for detecting and identifying faults [16]. The DI is based on the Kullback–Leibler information distance (KLID), the mean of the measured variables, and the range of the measured variables. The CD is derived based on the multivariate T^2 statistic. This article presents an approach based on the DI/CD that systematically utilizes a more complete set of feature representations, including the data-driven, causal connectivity-based, and propagation path-based features, for diagnosing known, unknown, and multiple faults.

The rest of this article is organized as follows. Section 2 describes the DI/CD-based algorithm for diagnosing known, unknown, and multiple faults. The proposed method is evaluated in Section 3 using data sets from a chemical plant simulator for the Tennessee Eastman Process. Section 4 summarizes the conclusions.

2. Methods

2.1. Modified distance and modified causal dependency

The modified distance (DI) and modified causal dependency (CD), which serve as the basis of the proposed diagnosis method for multiple and unknown faults, are briefly reviewed in this section. More details of the two techniques can be found in [16].

The DI is based on the Kullback–Leibler information distance (KLID), the mean of the measured variables, and the range of the measured variable. The DI is used to measure the similarity of the measured variable between the current operating condition and historical operating conditions. When the DI is larger than the predefined threshold, the variable is identified as abnormal with respect to the historical operating conditions. The KLID for the historical distribution of the variable q is defined by

$$f_{h,t}^q := I(p_{h,t}^q, 1) \tag{1}$$

where the historical distribution $p_{h,t}^q$ is constructed for data collected from time $t-b+1$ to t (b is the window size), $I(p_1, p_2) := \int p_1(x)\ln(p_1(x)/p_2(x))dx$ where $p_1(x)$ and $p_2(x)$ are two distributions, and the integral is calculated numerically. When $p_{h,t}^q$ is the uniform distribution, the value of $f_{h,t}^q$ is equal to zero.

With $f_{\bar{h},t}^q$ defined as the KLID of the historical distribution computed by using all n observations, the absolute difference between the current KLID $f_{r,t}^q$ and historical KLID $f_{\bar{h},t}^q$ for a fault is calculated as

$$\tilde{f}_{r,t}^q := \left| f_{r,t}^q - f_{\bar{h},t}^q \right| . \tag{2}$$

Similarly, the absolute difference between the current mean $m_{r,t}^q$ and historical mean $m_{\bar{h},t}^q$ is

$$\tilde{m}_{r,t}^q := \left| m_{r,t}^q - m_{\bar{h},t}^q \right| \tag{3}$$

and the absolute difference between current range $s_{r,t}^q$ and historical range $s_{\bar{h},t}^q$ is

$$\tilde{s}_{r,t}^q := \left| s_{r,t}^q - s_{\bar{h},t}^q \right| \tag{4}$$

where the mean and the range of the variable q at current time $t = T$ is

$$m_{r,t}^q := \frac{1}{b} \sum_{t=T-b+1}^{T} q_t \tag{5}$$

and

$$s_{r,t}^q := \max_{T-b+1 \le t \le T} q_t - \min_{T-b+1 \le t \le T} q_t \tag{6}$$

respectively.

The normalized KLID associated with the recent distribution and the historical distribution for the fault is defined by

$$F_{r,t}^q := \frac{\tilde{f}_{r,t}^q}{\text{mean}(\tilde{f}_{h,t}^q) + n_r \text{std}(\tilde{f}_{h,t}^q)} \tag{7}$$

where n_r is a constant used to specify the misclassification error (type-I error) which can be determined based on the historical data. A similar recent distribution and the historical distribution will result in $F_r^q < 1$.