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Multi-agent based collaborative fault detection and identification in chemical processes

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ABSTRACT

Fault detection and identification (FDI) has received significant attention in literature. Popular methods for FDI include principal component analysis, neural-networks, and signal processing methods. However, each of these methods inherit certain strengths and shortcomings. A method that works well under one circumstance might not work well under another when different features of the underlying process come to the fore. In this paper, we show that a collaborative FDI approach that combines the strengths of various heterogeneous FDI methods is able to maximize diagnostic performance. A multi-agent framework is proposed to realize such collaboration in practice where different FDI methods, i.e: principal component analysis, self-organizing maps, non-parametric approaches, or neural-networks are combined. Since the results produced by different FDI agents might be in conflict, we use decision fusion methods to combine FDI results. Two different methods – voting-based fusion and Bayesian probability fusion are studied here. Most monitoring and fault diagnosis algorithms are computationally complex, but their results are often needed in real-time. One advantage of the multi-agent framework is that it provides an efficient means for speeding up the execution time of the various FDI methods through seamless deployment in a large-scale grid. The proposed multi-agent approach is illustrated through fault diagnosis of the startup of a lab-scale distillation unit and the Tennessee Eastman Challenge problem. Extensive testing of the proposed method shows that combining diagnostic classifiers of different types can significantly improve diagnostic performance.

1. Introduction

Diagnosis of process faults in chemical processes has been an active area of research (Srinivasan, 2007). Successful identification of process faults at an early stage can increase the success rate of fault recovery during operations and prevent unnecessary shutdowns. Also, automatic detection and diagnosis of faults are necessary to prevent costly accidents by providing time critical diagnostic information to plant operators. In literature, several fault diagnosis methodologies have been proposed for fault detection and identification (FDI) in chemical processes (Venkatasubramanian et al., 2003a,b,c; Srinivasan et al., 2005a,b; Ng and Srinivasan, 2009a). Each FDI method has its strengths and shortcomings, which are process and fault dependant. A method that works well under one circumstance might not work well under another when different features of the process come to the fore. Combining FDI methods of different types is hence an attractive solution for monitoring processes operating under a wide range of operating conditions.

In addition to being adaptive towards different operating conditions, combining different FDI methods can also achieve higher diagnostic resolution by combining the strengths of existing FDI methods. It has already been shown in the pattern recognition literature that a judicious combination of classifiers generally outperforms a single one (Rahman and Fairhurst, 1999; Lin et al., 2003; McArthur et al., 2004). The main reason for combination of classifiers is that different types of classifiers can often complement one another and improve performance as a result of collaboration. When diagnosing faults in complex processes, designing a perfect classifier for all possible scenarios can be difficult, and combining different fault diagnostic methods is shown to be a good alternative wherein different features of heterogeneous diagnostic classifiers can be synergistically consolidated. To facilitate the integration of heterogeneous diagnostic classifiers, a multi-agent system is proposed in this paper to integrate various FDI methods. The organization of this paper is as follows: Section 2 provides the review of some previous work in the fields of FDI, decision fusion and agent-based methods.

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Section 3 describes the proposed multi-agent approach for collaborative FDI and the underlying decision fusion strategies. The proposed multi-agent with its decision fusion strategies are tested with two case studies, namely startup of a lab-scale distillation column and the Tennessee Eastman Challenge problem in Section 4 and Section 5, respectively.

1.1. Review of FDI methods

In general, existing FDI methods can be broadly classified into two categories namely qualitative model-based and quantitative model-based methods. Qualitative model-based methods include techniques such as trend analysis and expert systems. Trend analysis is based on the abstraction of process data into a set of trends (Cheung and Stephanopoulos, 1990). Monitoring is then performed on the identified trends, which are made up of primitives that describe the qualitative behavior of the process variables. Classical trend analysis approaches are based on monitoring an ordered set of primitives that describe the evolution of a process variable. When a fault occurs, process variables vary from their nominal ranges and exhibit trends that are characteristic of the fault. Hence, different faults can be mapped to their characteristic trend signatures. Extension of trend analysis through fuzzy reasoning is reported in Dash et al. (2003).

During transitions, each variable might display a different trend during different phases of the transition. There are also occasions where process exhibits different trends during transitions due to normal operating variations, thus complicating trend comparison. Classical trend analysis is therefore not sufficient to monitor transitions adequately. Sundarraman and Srinivasan (2003a, b) overcome the above problems through enhanced trends. Three types of matching degrees – shape matching degree, magnitude matching degree, and duration matching degree – were introduced to facilitate trend comparison during transition. The main shortcoming of trend analysis is that it is designed for monitoring individual variables. It does not take into account the correlation between the variables in the process.

Expert systems, or rule-based systems, use rules to perform monitoring. They are best suited to situations where plant operators have a good knowledge regarding the nuances of the transitions and the underlying process. Honda and Kobayashi (2000) used a fuzzy rule-based inference system for the direct control of batch operations. The process phase is first recognized by fuzzy inference, and then a fuzzy neural-network based control system is used to control the batch process. They illustrated their methods on mevalotin precursor production, vitamin B2 production, and sake mashing processes. In Muthuswamy and Srinivasan (2003), a rule-based expert system is developed for automation and supervisory control of semi-batch fermentation processes. They characterized transitions using features in process variables and represented them as multivariate rules. These rules track the process across phases and automatically detect the current active phase using online data. Different monitoring rules are formulated for each phase of a transition. The rule-based transition characterization method was shown to be robust to measurement noise and easily comprehendible to the operators. Nevertheless, rule-based systems are process specific; at times, it is hard to extract rules to adequately model complex processes.

First-principle models, statistical models, signal processing models, and neural-networks are clustered under quantitative model-based systems. Extensive coverage of quantitative model-based approaches for monitoring and diagnosing faults during steady-state can be found in Chen and Patton (1999) and Venkatasubramanian et al. (2003c). Quantitative models are built either from first-principles knowledge or from using input–output data. In Bhagwat et al. (2003a), a non-linear model-based approach was proposed to monitor process transitions. Estimation of process states and residuals was achieved through open-loop observers and Kalman filters. To address the issues arising from the discontinuous nature of transition, the scheme uses knowledge of the standard operating procedure and divides each transition into phases. For monitoring, each phase is associated with a model component and different filters and observers are selected for fault detection in that phase. However, accurate models of highly complex processes operating in multiple regimes are seldom available and difficult to develop, thus limiting their practical applicability. Multiple model-based approaches have therefore been used to model, control, and monitor transitions. In Bhagwat et al. (2003b), a multi-linear model-based fault detection scheme was proposed based on decomposition of operation of a non-linear process into multiple locally linear regimes. Kalman filters and open-loop observers were used for state estimation and residuals generation in each regime. Analysis of residuals using thresholds, faults maps, and logic-charts enabled on-line detection and isolation of faults.

Signal processing methods can be applied to analyze the normal/abnormal status of a process by comparing the online profile of process variables with those of previously known runs. The underlying methods perform time synchronization between process signals from different runs before comparing them based on predefined similarity metrics. Methods for signal processing include dynamic time warping (DTW) and dynamic programming (DP). Applications of DTW for process monitoring can be found in Gollmer and Posten (1996) and Kassidas et al. (1998a, b). One known shortcoming of DTW is its high computational cost, which grows exponentially with the length of process data. This can be minimized by using landmarks such as peaks or local minima in the signals to reduce the complexity of signal comparison (Srinivasan and Qian, 2005, 2007). These landmarks, called singular points, can be used to decompose a long continuous signal into multiple, short, semi-continuous ones. However, one known shortcoming of DTW algorithm is the essential requirement that the starting and ending points of the signals to be compared should coincide. Such shortcomings obviate their direct practice for online applications since the points in the historical database that should be matched with the starting and ending points of the online signal are unknown. To overcome these shortcomings, Srinivasan and Qian (2006) proposed dynamic locus analysis which is an extension of Smith and Waterman (1981) discrete sequence comparison algorithm for online signals comparison.

With the increasing availability of inexpensive sensors, the number of measured variables for most industrial processes easily ranges in thousands. This has lead to the popularity of multivariate statistical methods, which bring forth powerful means to monitor transitions. Principal components analysis (PCA) is one such multivariate dimensionality reduction technique that is widely used for developing data-driven models (Jackson, 1991). Applications of PCA and its variants for process monitoring can be found in MacGregor and Kourti (1995) and Chen and Liu (2002). Most of the reported work in multivariate statistical analysis is directed to processes where the correlation between the process variables remains the same. These approaches are not directly applicable to transitions due to statistical non-stationarity and time-varying dynamics. In order to overcome this, an extension called dynamic PCA (DPCA) has been proposed (Ku et al., 1995). In Srinivasan et al. (2004), DPCA has been used to classify process states based on historical operating data. Process data is first segmented into modes and transitions. Steady-state modes are identified by using a moving window approach which is capable