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Cognitive fault diagnosis in Tennessee Eastman Process using learning in the model space

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ABSTRACT

This paper focuses on the Tennessee Eastman (TE) process and for the first time investigates it in a cognitive way. The cognitive fault diagnosis does not assume prior knowledge of the fault numbers and signatures. This approach firstly employs deterministic reservoir models to fit the multiple-input and multiple-output signals in the TE process, which map the signal space to the (reservoir) model space. Then we investigate incremental learning algorithms in this reservoir model space based on the "function distance" between these models. The main contribution of this paper is to provide a cognitive solution to this popular benchmark problem. Our approach is not only applicable to fault detection, but also to fault isolation without knowing the prior information about the fault signature. Experimental comparisons with other state-of-the-art approaches confirmed the benefits of our approach. Our algorithm is efficient and can run in real-time for practical applications.

1. Introduction

With the development of chemical industry, chemical processes become more complex. The product efficiency and consistency become essential. Therefore, on-line monitoring and fault diagnosis are gaining more attention for produce quality and plant safety. In recent years, there has been a lot of research in the design and analysis of fault diagnosis schemes for different dynamic systems (for example, Chen and Patton, 1999; Gertler, 1998). A significant part of the research has focused on linear dynamical systems, where it is possible to obtain rigorous theoretical results. More recently, considerable effort has been devoted to the development of fault diagnosis schemes for nonlinear systems with various kinds of assumptions and fault scenarios (Zhang et al., 2002, 2005; Yan and Edwards, 2007).

These traditional fault diagnosis approaches rely, to a large degree, on the mathematical model of the "normal" system. If such a mathematical model is available, then fault diagnosis can be achieved by comparing actual observations with the prediction of the model. Most autonomous fault diagnosis algorithms are based on this methodology. However, for complex chemical processes operating in dynamic environments, such mathematical models may not be accurate or even unavailable at all. Therefore, it is necessary to develop cognitive fault diagnosis methods based on the real-time data.

In a typical chemical process, there are a large number of input variables, measurement (output) variables in chemical plants. Some of these variables are highly correlated, which increases the difficulty to extract useful information in the diagnosis process. For example, a significant change in output variables may be driven by input variables or by faults. Most of the existing data-driven fault diagnosis approaches that rely on detection of output concept drift using signals cannot deal with this kind of situation. The usual methodology is to employ an estimator, such as a neural network, to approximate the mapping from input variables to output variables. Then, the difference between the exact observations and the predicted outputs are compared for fault diagnosis. As this methodology has employed the estimator to approximate the input-output mapping, it may reduce the false alarm rate. However, the estimator can only produce accurate results when given sufficient data in all kinds of situations, such as in the normal regime and various fault scenarios. In a practical chemical process, it is expensive to obtain all such data. The absence of training data would result in low fault detection rate.

To address these problems, we introduce a novel "learning in the model space" framework for dealing with fault detection and fault isolation when no or very limited knowledge is provided about the underlying system (Chen et al., 2014). In this framework, we do not assume that we know the type, the number or the functional form

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of the faults in advance. The core idea is to transform the signal into a higher dimensional "dynamical feature space" via reservoir computation models and then represent varying aspects of the signal through variation in the linear readout models trained in such dynamical feature spaces. In this way parts of the signal captured in a sliding window will be represented by the reservoir model with the readout mapping fitted in that window.

Reservoir computing (RC) (Lukoševičius and Jaeger, 2009) is a class of state space models based on a "fixed" randomly constructed state transition mapping, realized through so-called reservoir and an trainable (usually linear) readout mapping from the reservoir. In our formulation, the underlying reservoir will be the *same* throughout the signal – the differences in the signal characteristics at different times will be captured solely by the linear readout models and will be quantified in the function space of readout models.

We assume that for some sufficiently long initial period the system is in a 'normal/healthy' regime so that when a fault occurs the readout models characterizing the fault will be sufficiently 'distinct' from the normal ones. A variety of novelty/anomaly detection techniques can be used for the purposes of detection of deviations from the 'normal'. In this paper we will use one-class support vector machines (OCS) (Schölkopf et al., 2001) in the readout model space. As new faults occur in time they will be captured by our incremental fault library building algorithm operating in the readout model space.

The main contributions of this paper include:

- This paper *for the first time* investigates the *cognitive fault diagnosis on the TE process* without prior knowledge of the fault numbers and types. To our knowledge, there is no existing work on *cognitive fault diagnosis* on the TE process. All existing work on fault diagnosis on the TE process relies on the assumption that all the fault patters are known in advance.
- This paper also studies the strategy to dynamically construct fault dictionary in real time.

The rest of this paper is organized as follows. The background and the related work are reviewed in Section 2. Section 3 introduces deterministic reservoir computing and the framework of "learning in the model space", followed by the incremental one class learning algorithm for cognitive fault diagnosis in Section 3.2. The experimental results and analysis on Tennessee Eastman Process are reported in Section 4. Finally, Section 5 concludes the paper and presents some future work.

2. Background and related work

The fault diagnosis procedure can often be investigated in three steps: (i) fault detection is the process of determining whether a fault has occurred or not; (ii) fault isolation deals with the issue of determining the location/type of fault; and (iii) fault identification provides an estimate of the magnitude or severity of the fault. In some cases, the issues of fault isolation and fault identification are interwoven, since they both deal with determining the type of fault that has occurred.

Most automated fault diagnosis algorithms are based on the available mathematic models. However, for complex engineering systems operating in uncertain environments, such mathematical models may not be accurate or even unavailable at all. Therefore, it is necessary to develop cognitive fault diagnosis methods based on the observed data.

The data driven approaches are popular fault diagnosis methods when the system models are unclear, especially in distributed systems. A general learning methodology for fault diagnosis of nonlinear systems was first developed by Polycarpou and Helmicki (1995), where the stability and approximation properties of the learning scheme were rigorously investigated for the ideal case without modelling uncertainty. There have been other learning based approaches to fault detection and diagnosis, e.g. Vemuri and Polycarpou, 1997; Palade and Bocaniala, 2010; Venkatasubramanian et al., 2003; Kankar et al., 2011. Neural networks were used as learning algorithms for fault detection and diagnosis, e.g. Vemuri and Polycarpou, 1997; Venkatasubramanian et al., 2003; Palade and Bocaniala, 2010. In 2011, Barakat et al. (2011) proposed to use self adaptive growing neural network for faults diagnosis. They applied wavelet decomposition and used the variance and kurtosis of the decomposed signals as features to train neural networks.

In fault detection and diagnosis, Tennessee Eastman (TE) process, created by the Eastman Chemical Co., has been widely used as a benchmark for evaluating process diagnosis methods (Fig. 2). In 2009, Yélamos et al. (2009) proposed to use support vector machines for fault diagnosis in chemical plants. In a specific application, neural network and support vector machines have been employed to identify ball bearings faults (Kankar et al., 2011). Principal component analysis (PCA) (Raich and Cinar, 1995, 1997; Kano et al., 2000), multiway PCA (Chen and McAvoy, 1998), partial PCA (Huang et al., 2000), nonlinear dynamic PCA (Lin et al., 2000), pattern recognition (Kassidas et al., 1998), Fisher discriminant analysis (FDA) (Chiang et al., 2004), PCA-wavelet (Akbaryan and Bishnoi, 2001), steady-state-based approach (Chen and Howell, 2002), support vector machines (SVM) (Chiang et al., 2004), and PCA-QTA (qualitative trend analysis) (Maurya et al., 2003) have all been applied to the TE process. Most of the previous methods are based on multivariate statistics, and several studies have used nonlinear or dynamic models to consider process dynamics and nonlinearity (Chen and McAvoy, 1998). Although data driven methods show good diagnostic performance, they either assume that all the fault patterns are known a priori, or are inapplicable for unknown faults, which is unrealistic for practical systems operating in an uncertain environment,

The fault diagnosis framework (Chen et al., 2014) used in this paper is able to identify new faults by employing the incremental one-class learning approach in the model space. Learning in the model space (Chen et al., 2014) is naturally applicable to the current industrial MIMO system, and the framework is robust to imperfection in data/signal, such as missing values, high dimensionality, etc.

3. The framework of learning in the model space

This section introduces the recently proposed "learning in the model space" framework (Chen et al., 2014), which includes multiple-input and multiple-output (MIMO) signal simulated by deterministic reservoir models, and the learning stage using incremental one-class learning with the 'model distance' as the input features.

3.1. Learning in the model space

Recently, Chen et al. (2014) proposed to use deterministic reservoir computing (DRC) (Rodan and Tiňo, 2012) to represent MIMO signal segments and to use incremental one-class learning for fault diagnosis. Learning in the model space is to use models fitted on parts of data as more stable and parsimonious representations of the data. Learning is then performed directly in the model space, instead of the original data space.

Reservoir computing (RC) (Lukoševičius and Jaeger, 2009) is a class of state space models based on a "fixed" randomly constructed state transition mapping, realized through so-called reservoir and an trainable (usually linear) readout mapping from the reservoir.