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A diagnostic method based on clustering qualitative event sequences

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ABSTRACT

A diagnostic algorithm is described in this article that is based on clustering qualitative event sequences called traces. A sufficient number of training traces are used instead of an internal model to specify the faulty models of the system. The diagnosis consists of two phases. In the off-line training phase diagnostic clusters representing nominal and faulty behavior are formed from the set of training traces, while the centroids of these clusters are stored. Arbitrary measured traces in the on-line diagnosis phase are compared with the centroids, to recognize the most probable faulty scenario for the trace. The effects of different mapping functions and different qualitative ranges on the clustering are investigated, and the diagnostic resolution of the method is compared and discussed using a simple process system. A diagnostic case study using the benchmark of Tennessee Eastman process (TEP) is utilized to illustrate the efficiency of the proposed method.

1. Introduction

Early and accurate fault diagnostics is one of the most important challenges during the operation of modern day process systems. Primeval fault mitigation and isolation due to proper diagnostics plays a crucial role in avoiding huge losses and plant breakdowns caused by the consequences of initially smaller and isolated but propagating failures discovered too late.

Due to the high importance of the field, the relevant literature is extensive with model-based diagnostic methods traditionally being the most widespread. Process fault diagnostics based on process and fault models had been widely described by Venkatasubramanian et al. (2003a,b,c) in review articles. According to Venkatasubramanian et al. (2003b), model based a priori knowledge can be broadly classified as quantitative and qualitative. Fault detection using these qualitative models can be performed by using expert systems with different kind of reasoning, using signed directed graphs (SDGs) for modeling cause-effect relations (for instance in Vedam and Venkatasubramanian, 1997) or fault trees describing the relations between primary events to top level events or hazards. Fault propagation analysis (Gabbar, 2007) can be also used for the identification of faults, causes and consequences in a systematic manner.

Qualitative physics is also used for process system modeling as a common sense reasoning about physical systems. This approach is based on qualitative or ordinary differential equations describing the process system to be diagnosed. These qualitative dynamic models together with many different methods (like the one in Tóth et al., 2014) use an abstract hierarchy of process knowledge which is based on decomposing the process system into subcomponents, in order to decrease computational complexity and speed up the diagnostics task.

The information collected by hazard identification can be also regarded as a special form of process models. An attempt to unite the diagnostic information stored in HAZOP and FMEA analysis results, called the blended HAZID methodology was described in Németh and Cameron (2013) together with its use for process system diagnosis tasks. This approach has been further extended in Guo and Kang (2015) using dynamic fault trees.

Fault diagnosis includes two sub-steps even in the most general case: fault detection and fault isolation or identification. While the first sub-step needs an accurate model of the process in its normal, i.e. non-faulty operation mode, fault models of the considered faulty modes are needed for the latter. Therefore, the most important aspect of a fault diagnostics algorithm for process systems is the fault model which requires significant amount of human expertise and work to set up and maintain. Our main aim in this article is to suggest a data-driven diagnostic procedure which may require less amount of human assistance as compared to a model-based approach during set-up and operation and still remains feasible as a fault diagnostic method. While a satisfactory model of a

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possibly complex process system in each of its considered faulty mode is needed that requires skilled human efforts, informative enough observed data set that are annotated with the recognized fault(s) by the plant operators may form the basis of a data-driven diagnostic procedure.

In the last review article of the series by Venkatasubramanian et al. (2003c) on process systems diagnosis, process history based methods are surveyed. Instead of an a priori model, these methods require a large amount of historical process data, and they can be classified by the way they extract information from the process data (this operation is called feature extraction). Feature extraction can be qualitative (for example using rule-based expert systems or qualitative trend analysis) and quantitative (using statistical methods, such as PCA or neural networks).

For describing arbitrary output signal values qualitative trend analysis (QTA) can be used, by comparing qualitative trends of nominal and actual signal values (a good example can be found in Maurya et al., 2005). In some newer results (in Maurya et al., 2007), these methods have been even combined to perform fault diagnosis.

A special type of historical process data are the so called alarms, the timed sequence of which has been utilized for early fault detection and diagnosis in Agudelo et al. (2013). These alarm sequences can be also regarded as event logs. In van der Aalst et al. (2007) a process mining tool called ProM is described which is capable of discovering process models in the form of Petri Nets, using event logs collected from process systems.

This tool also supports conformance checking, verification, model extension and transformation as well as model discovery. A ProM extension described in Alves de Medeiros et al. (2008) uses *K*-means clustering for categorizing event logs prior to mining them, in order to achieve faster operation. In a slightly different approach described in Rozinat et al. (2008), Petri nets are used to build up models from event sequences, and the fitness and appropriateness of the model is calculated.

In the approach described in this paper similar metrics to ProM are used to perform the validation (in the way the fitness of the model is calculated) after an initial training phase performed on the historical process data. As a technique used thoroughly in machine learning, clustering is widely used in systems used for process diagnosis. The algorithm described in this paper is based on the *K*-means clustering algorithm (described in Alpaydin, 2010b) like a modeling approach described in Alves de Medeiros et al. (2008). Different other approaches are using the fuzzy c-means clustering (FCM, described in Alpaydin, 1998), a method based on the concept of fuzzy sets and logic (described originally in Zadeh, 1975). For example, fuzzy c-means clustering for fault classification is reported in Mercurio et al. (2009) and Petković et al. (2012) while it is used for process control in Kim and Kim (2014).

The most widely used quantitative feature extraction procedures use statistical methods (e.g. PCA or PLS) for process monitoring and fault detection, for which good review papers have appeared recently, see Yin et al. (2012), Qin (2012) or MacGregor and Cinar (2012). A recent improvement of the PLS method capable of detecting small faults have been reported in Harrou et al. (2015). However, these methods usually assume steady-state operation condition of the system to be diagnosed, and fail during transient operations. This fact and the need for diagnosing process systems outside of their steady-state regime have motivated our research to overcome this constraint.

The structure of this paper is as follows. First, basic notions about qualitative event sequences (traces) and their representations are introduced. After that, the proposed diagnostic procedure is described in detail, finally the diagnostic capabilities of the algorithm are demonstrated using a simple and composite case study (the Tennessee Eastman Challenge Process).

2. Qualitative events, traces and their distances

In case of a process system working under transient conditions (i.e. it is not steady-state) its operation can be described as sequences of events. These events refer to the actual values of measured quantities of the system at specific times, such as the values of the *system inputs* including the possibly discrete valued (on/off or open/close) states of the actuator elements (for example pumps or valves) and the values of the *system outputs* which are the values of sensors (such as level or pressure sensors).

2.1. Events with qualitative range spaces

System inputs and outputs are signals, i.e. time-dependent quantities (as described in Hangos et al., 2004). Their range space can naturally be discrete (such as open or close for a two-state valve) or real (a positive real value for a pressure signal).

In case of uncertain values for a real valued measured signal, one can describe the actual value using a qualitative range space, which is a set of ordered mutually disjoint set of real intervals. The number and the actual end-point set of these intervals (i.e. the resolution of the qualitative range set) depend on the accuracy of the measured signals and on the desired accuracy of the diagnostic results. In order to be able to investigate the effect of the resolution on the diagnostic accuracy, we define and use two different qualitative range sets in this paper.

First we define a simple natural set of intervals that fits to positive valued signals, such as temperatures or levels. One may associate verbal *labels* to the intervals following the normal operational value of the signal as follows: "*N*" stands for the normal range, "0", "*L*" and "*H*" denote the empty, low and high but acceptable values (still inside normal ranges), respectively, while "*e*−" and "*e*+" refer to values which are outside nominal ranges, respectively. Formally, this basic *qualitative range set* is described in the following way:

$$Q = \{e-, 0, L, N, H, e+\} \tag{1}$$

It is possible to create a refined qualitative range set from the qualitative set Q in Eq. (1) by placing a new qualitative value between two already existing ones. Such *refined qualitative range set* is given below

$$Q_{refined} = \{e-, -0, 0, 0L, L, LN, N, NH, H, H+, e+\} \tag{2}$$

with the newly introduced labels "−0" small negative values, "0*L*" very low, "*LN*" a bit low, "*NH*" a bit high, "*H*+" very high.

One can further refine the qualitative range set by adding new intermediate values and achieve the range space of real values in the limit.

The range space of binary discrete valued signals, such as the status of a valve with two states, can be described by the range space

$$\mathcal{B} = \{0, 1\} \tag{3}$$

where "0" can be associated to the closed and "1" to the opened status.

The qualitative sets defined in Eqs. (1) and (2) can be also seen as a boundary case of a fuzzy set (as defined in Zadeh, 1975) which does not contain fuzziness, in this case every membership function has a constant value for a defined interval and those intervals does not overlap each other, like ordinary fuzzy sets do.