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Design of multivariate alarm systems based on online calculation of variational directions☆

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ABSTRACT

Alarm systems are critically important for safety and efficiency of industrial plants, but are severely suffering from alarm overloading. This paper proposes a method to design a multivariate alarm system based on variational directions of involved process variables, in order to alleviate the severity of alarm overloading. By using adaptive time scales, time gradients of signals are extracted to calculate variational directions in an online manner. Adaptive time scales are determined from a function between time scales and volatilities of process variables. Alarms arise at the moment that a nominal relationship of variational directions among process variables is invalidated. Numerical and industrial examples illustrate the effectiveness of the proposed method.

1. Introduction

Modern industrial plants are usually monitored by computerized alarm systems, which play a critically important role for safe and efficient operations of industrial plants (ISA, 2009; EEMUA, 2013). However, many existing industrial alarm systems are suffering from alarm overloading (Bransby and Jenkinson, 1998; Rothenberg, 2009; Hollifield et al., 2011), i.e., there are too many alarms appearing in a short time period to be promptly handled by plant operators.

The phenomenon of alarm overloading is clearly revealed from Table 1 based on a study of 39 industrial plants from oil and gas, petrochemical, and power industries (Rothenberg, 2009). The performance metrics such average alarms per day for these industrial plants are much worse than the recommended performance benchmarks (the second column in Table 1) from the Engineering Equipment and Materials Users' Association (EEMUA). Among the occurred alarms, there are many nuisance alarms that are not associated with any actual abnormalities. Due to "cry wolf" effects caused by nuisance alarms, operators may have little trust on alarm systems and fail in noticing informative alarms that are associated with abnormal conditions. One main reason of nuisance alarms is that the most common way of arising alarms in process industries is to compare the measurements of a single process variable with a high or low alarm threshold, and related process variables are not taken into account in designing alarm systems (Wang et al., 2016). Thus, the design of multivariate alarm systems is an important research topic in alleviating the severity of alarm overloading.

The essence of designing effective multivariate alarm systems is to exploit some features of involved multiple process variables to detect abnormal conditions in an online manner. Brooks et al. (2004) compared current data points to a pre-defined normal operating zone of multiple process variables via a geometric process control technique, and visualized dynamic alarm thresholds in parallel coordinates. Charbonnier et al. (2005) and Charbonnier and Portet (2012) extracted the trends of process variables for complex process monitoring and fault diagnosis. Izadi et al. (2009) and

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Table 1 – Cross-industry study (Rothenberg, 2009).

	EEMUA	Oil-gas	PetroChem	Power
Average alarms/day	144	1200	1500	2000
Peak alarms/10 min	10	220	180	350

Kondaveeti et al. (2009) applied multivariate statistics such as principal component analysis to generate alarms more efficiently. Gupta et al. (2013) integrated multiple techniques such as wavelet analysis and principal component analysis to rationalize alarm thresholds of process variables to alleviate noise effects and detect faults earlier. Zhu et al. (2014) proposed dynamic alarm thresholds being adaptive for different pre-defined operating stages varying with time. Alrowaie et al. (2014) applied particle filters for multivariate nonlinear stochastic systems to design alarm thresholds. Zang and Li (2014) and Han et al. (2016) optimized alarm thresholds by minimizing false and missed alarm probabilities on the basis of joint probability densities of process variables in the normal and abnormal conditions.

Variational directions of related process variables are exploited here as the features to detect abnormal conditions. This idea is based on an observation on how industrial plant operators find abnormal conditions. Let us take a variable frequency pump as an example. It can be easily observed that the outlet flow rate is always increasing or decreasing in a synchronized manner with the pump speed, when the pump works in normal conditions. This observation is guaranteed by physical laws of the pump operation. Hence, if the outlet flow and speed of a variable frequency pump are found moving in opposite directions, then there must be something wrong in the pump operation. Thus, by looking at the directions of variations in the outlet flow rate and the pump speed, industrial plant operators are able to judge whether the pump is in the abnormal condition or not.

Variational directions can be obtained by qualitative trend analysis (QTA) methods that extract the increasing, decreasing or steady trends of signals. Several QTA methods have been proposed in literature. Signals are approximated by several piecewise linear segments (Keogh et al., 2001; Charbonnier et al., 2005; Charbonnier and Gentil, 2007; Charbonnier and Portet, 2012) or high-order polynomials (Savitzky and Golay, 1964; Maurya et al., 2010). Splines methods and wavelet methods decompose signals into different scale bases (Vedam et al., 1998; Flehmig et al., 1998; Flehmig and Marquardt, 2006). Clustering methods use a fuzzy C-means clustering technique to identify different trends (Melek et al., 2005). Primitives methods represent signals by a combination of primitives in series whose local trends are pre-defined (Janusz and Venkatasubramanian, 1991; Rengaswamy and Venkatasubramanian, 1995; Colomer et al., 2002). However, the above-mentioned methods may have two limitations:

1. Some online methods modify the extracted trends in the past after the most recent trends are updated, so that they are not implemented in a real online sense (see e.g., Keogh et al., 2001; Charbonnier et al., 2005; Charbonnier and Gentil, 2007; Maurya et al., 2010; Charbonnier and Portet, 2012). Taking the sliding window method in Keogh et al. (2001) as an example, this method fits a signal using a linear segment growing with the time until the fitting error becomes larger than a threshold, and then updates the linear segment by restarting the fitting procedure. As a numerical illustration, Fig. 1 shows the time sequence plots of a signal $x(t)$ (upper subplot) and its backward difference $x_d(t) = \hat{x}(t) - \hat{x}(t-1)$ (lower subplot), where $\hat{x}(t)$ is an approximated signal of $x(t)$ obtained by the sliding window method. The extracted trends of all samples before the time instant $t = 100$ are larger than zero; however, the trends are modified to take negative values at the time instant $t = 200$. The extracted trends before $t = 100$ and after $t = 200$ are erroneously inconsistent.
2. Few methods are able to adapt extracted trends to the coexisted sharp and smooth variations in signals. For sharp variations, narrow time windows or equivalently smaller time scales should be used in order to detect the changes of trends promptly; by contrast, for smooth variations, larger time windows or larger time scales should be exploited in order to reduce negative effects of noises on the trend extraction. As an illustration, Example 1 in Section 4 later illustrates this limitation for a widely used method, the Savitzky–Golay (S–G) filter (Savitzky and Golay, 1964).

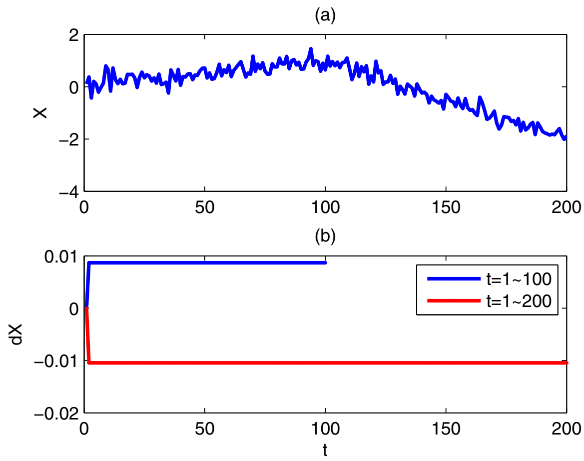

Fig. 1 – (a) The time sequence plot of the signal $x(t)$, (b) the time sequence plot of the difference signal $x_d(t)$ for $t \in [1, 100]$ (upper) and that for $t \in [1, 200]$ (lower).

This paper proposes a new method to design a multivariate alarm system based on variational directions of involved process variables. Due to the above two limitations, the existing QTA methods are not adopted here to calculate the variational directions. Instead, a so-called adaptive time gradient (ATG) approach is formulated to calculate the time gradients of signals and the variational directions by using adaptive time scales. The key step of the ATG approach is to determine adaptive time scales from a function between time scales and volatilities of signals. The function parameters are estimated from training data sets. Compared to the existing QTA methods, the ATG approach is adaptive in time scales and is online in a real sense. Alarms are ready to arise, when the variational directions have a conflict with a nominal relationship of variational directions among process variables in normal conditions obtained from some process knowledge. To the best of our knowledge, this paper perhaps is the first one in literature to exploit the variational directions of related process variables in designing alarm systems.

The rest of the paper is organized as follows. Sections 2 and 3 present the main idea and the details of the proposed method. Sections 4 and 5 respectively provide numerical and industrial examples to illustrate the effectiveness of the proposed method. Section 6 concludes the paper.