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Fault template extraction to assist operators during industrial alarm floods

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ABSTRACT

In industrial systems, a fault occurring on a process can create an alarm flood, a succession of alarms raised at a rate per minute so high it overwhelms the process operator in charge of the monitoring of the process. In this paper, a method to extract fault templates from a set of alarm lists raised on the occurrence of several faults is proposed. Alarm lists generated by the same fault are condensed into a weighted sequential fault template formed of the sequence of alarms the most frequently produced on the occurrence of the fault. Each alarm is weighted according to its relevance to diagnose the fault. It is further shown how the fault templates can be used to extract relevant information on the alarm system and be used by operators as guidelines for fault diagnosis. Moreover, an on line fault isolation method using a weighted sequential similarity measure is proposed. The results obtained by the method on a data set formed of alarm lists raised by the control system of the CERN LHC connected to a simulator of one of the LHC processes are presented and discussed.

1. Introduction

To ensure safety and productivity, industrial systems are nowadays closely monitored by operators using SCADA systems. A SCADA system is made of different layers: a field layer formed of sensors and actuators; a control layer where control algorithms are processed and alarms are generated; and a supervision layer where the valuable information, such as sensor values and alarms, is displayed to the operators. An alarm is a binary value that informs the operator that an abnormal situation has occurred. It may be caused by a process key variable crossing a pre-fixed threshold or by an equipment failure. Alarms are integrated in the control system. They are in general configured during the control conception stage or very early in the plant operation.

Industrial plants are dynamics systems, formed of inter-connected sub-systems, with a high degree of automation. With the development of new sensors and computer based control systems, alarms are very easy to design. Thus, their number has tremendously increased these last 30 years. The counter part of this fact is the high number of alarms that may be raised. When a fault occurs on a process, operators are often faced with a situation where tens or hundreds of alarms are raised in a short time. This situation is known as an alarm flood. A definition was given by the industrial standard ANSI/ISA-18.2 (ISA, 2009). An alarm flood occurs when more than 10 alarms are raised within a 10-minute time period. Alarm flooding is unfortunately a very common phenomenon. (Hollifield and Habibi, 2011) report about 14.6 alarm floods a day during an 8 weeks study. Alarm floods are obviously stressful situations for the operator, especially for the non-expert one. The alarm rate is so high that he/she does not have the time to analyze in depth the alarm list displayed, to make a diagnosis.

Two research axes to reduce the operator cognitive overload during alarm floods can be found in the literature. The first axis is to propose methods to detect irrelevant alarms raised by an existing alarm system, so as to reduce the amount of information displayed to the operator (Beebe et al., 2013; Izadi et al., 2009). The second axis is the development of methods able to support the operator in his decision making during the alarm flood. The methods are generally data driven. They make use of available historical alarm data bases.

- The first axis consists in the detection of unnecessary alarms, i.e. alarms that do not bring relevant information on the process state, so as to improve the performances of an alarm system. Chattering alarms are alarms that altern between normal and abnormal states during a short period of time. (Naghoosi et al., 2011; Kondaveeti et al., 2013) propose solutions to detect and

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remove them. Related alarms are alarms that are just the consequences of other alarms. They systematically appear in a short period of time or after a preceding alarm because they are related to the same event. (Salah et al., 2013) present a very complete survey of alert correlation techniques, describing the different methods used in different application fields from networks communication to industrial process monitoring to detect related events. Alarms may be represented by sequences, a set of ordered alarms. Sequential pattern mining methods may be used to group the sequences using a similarity measure (Wang et al., 2015; Vogel-Heuser et al., 2015) or an index measuring the frequency of occurrence of the sub sequence (Mannila et al, 1997; Dousson and Vu Duong, 1999). Alarms may be represented as time series. In this case, the time separating one alarm from the other is taken into account, contrary to sequential Mining. The methods look for alarms that are correlated in time i.e. they systematically appear with some given event or alarm in a given period of time (Folmer and Vogel-Heuser, 2012; Folmer et al, 2014; Chen and Lee, 2011; Yang et al, 2012). Association rule mining has also been used to discover explicit rules describing the appearance of a successive subset of alarms and thus discover propagated alarms (Tong and Guo, 2013; Li and Li, 2010). Graphical tools may also be used to discover visually related alarms (Laberge et al., 2014; Kondaveeti et al, 2010; Kondaveeti et al, 2012). With these different methods, alarms may be grouped into larger classes (Perdisci et al, 2006) or they may be cleaned up to reduce the information displayed to the operator.

- The second axis of research to reduce the operator's overload aims at supporting the operator during an alarm flood by proposing a cause to the alarm flood i.e. making an automatic diagnosis of the process. Some methods do not consider the order of appearance of the alarms. The decision is made with the alarms present (or absent) in the alarm list. Classifiers, such as neural networks or decision trees, are learnt from the historical data base. The input data is a binary vector representing the alarms present in the alarm list and the outputs are the different faults that may occur on the process (Ganyun et al, 2005; Charkaoui, 2005; AL-Jumah and Arslan, 1998; Negnevitsky and Pavlovsky, 2005; Stacchini de Souza et al, 2004; Chen et al., 2011). Another solution is to use pattern matching approaches. Binary vectors representing the alarm flood are compared with vectors of faults stored in the data base using simple similarity measures such as the Hamming distance, the Jaccard distance (Ahmed et al, 2013), or more complex ones (Charkaoui et al., 2005). The flood is assigned to the most similar fault. The order of appearance of the alarms can also be used to diagnose a fault. In this case, the alarm flood is represented by a sequence of alarms. Decision models using pattern recognition methods can be learnt, such as Bayesian networks, Petri nets, Hidden Markov models or abductive Reasoning Networks (Yamaguchi et al., 2012; Chen et al., 2012; Sun et al., 2012; Lefebvre and Leclercq, 2011). The input is a sequence of alarms representing the flood, the output is the fault assigned to the flood. These methods are able to extract the causal relationships between the alarms in an alarm flood. Pattern matching methods using symbolic sequence alignment methods, such as Dynamic Time Warping, or the Smith–Waterman or Needle-Man and Wunsch algorithms, to measure the similarity between alarms sequences were used as a mean to recognize alarm floods generating the same alarms in the same order (Ahmed et al., 2013; Cheng et al., 2013; Charbonnier et al., 2104).

This paper presents a method to assist process operators confronted with an alarm flood. Meaningful information-fault template – is automatically extracted from an historical data set formed of alarm lists. Each alarm list is formed of the alarms raised by the control system from the beginning of the alarm flood to its end. Several alarm lists recorded on the occurrence of the same fault are supposed to be available. Fault templates are created as a mean to represent a fault with a unique signature. The fault templates are used off-line to extract valuable feed-back information on the alarm generation process and on-line to support the operator when an alarm flood is occurring, by using a similarity measure between the unknown alarm flood and the fault templates.

In this paper, an alarm list is represented in two different ways: as a sequence of alarms and as a binary vector representing the alarms present (and absent) in the alarm list. A sequential and a vectorial template are extracted for each fault present in the data base. The sequential template is the succession of alarms that are present in the same chronological order in at least half of the alarm lists generated by the fault. It is extracted using a symbolic sequence alignment algorithm, the Needleman and Wunsh algorithm, widely used in bio-informatics. The vectorial template is formed of two terms: a binary vector, where '1s' represent the alarms present in at least half of the alarm lists generated by the fault, associated to a vector assigning weights to each alarm. The weight estimates the relevance of each alarm in the fault template, compared to another set of faults. It is formed of two terms, ranging from 0 to 1, one expressing how random the appearance of the alarm is when the fault occurs and the other one clearly expressing the probability that the alarm is not raised when other faults occur. These weights have a very clear meaning. They can be easily understood by the operators.

The sequential template and the weight vector are combined to form the weighted sequential fault template. The fault template can be displayed as a sequence where each alarm is presented in chronological order. The shape and color of each alarm forming the template is changed depending on its weight. The weighted sequential fault template provides some guidelines to the operator. It indicates her/him which alarms he should focus on to diagnose the fault and when to expect them. Both templates, sequential and vectorial, can be used to evaluate the diagnosability of a fault from its alarm list. Moreover, a weighted similarity measure is proposed and used to assist the operator confronted to an alarm flood. The similarity between the sequence of alarms generated by the unknown fault and the weighted sequential fault templates is calculated and a list containing the most similar faults is proposed to the operator. The method is applied on a data base formed of alarm lists generated by a simulator of one of the CERN Large Hadron Collider systems – the gas system which provides the particles detector with a mixture of gasses. The simulator is directly connected to the real CERN SCADA system, which creates the alarm list.

The outline of the paper is as follows. Section 2 describes the method developed in this paper. At first, the way both sequential and vectorial templates are extracted is presented. Then, it is shown how the templates can be used to extract knowledge and be a decision support tool for operators confronted to alarm floods. In Section 3, the data set used to evaluate the method is presented. The data set is formed of several alarms lists generated by the SCADA system of the CERN's LHC connected to a simulator of the gas system. In Section 4, the knowledge extracted on the gas system alarm system from the data set is presented and discussed. The ability of the method to diagnose a fault on line is further evaluated.