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Using Bayesian networks for root cause analysis in statistical process control

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ABSTRACT

Despite their fame and capability in detecting out-of-control conditions, control charts are not effective tools for fault diagnosis. There are other techniques in the literature mainly based on process information and control charts patterns to help control charts for root cause analysis. However these methods are limited in practice due to their dependency on the expertise of practitioners. In this study, we develop a network for capturing the cause and effect relationship among chart patterns, process information and possible root causes/assignable causes. This network is then trained under the framework of Bayesian networks and a suggested data structure using process information and chart patterns. The proposed method provides a real time identification of single and multiple assignable causes of failures as well as false alarms while improving itself performance by learning from mistakes. It also has an acceptable performance on missing data. This is demonstrated by comparing the performance of the proposed method with methods like neural nets and K-Nearest Neighbor under extensive simulation studies.

1. Introduction

Root cause analysis (RCA) is targeting at identifying the causes of problems in processes for directing counteractive actions (Rooney & Heuvel, 2004). Control charts typically do not have this feature; however non-random patterns on the chart can be used as a source for RCA (Doty, 1996; Montgomery, 2005; Smith 2004). However, large number of possible relations among patterns and causes makes the process of cause/s identification difficult. Certain information from the process (at the time of change) can be used in accompany with chart patterns to simplify this process. As a simple example, if we know from pattern analysis that either machine condition or the quality of input-material has caused an out-of-control situation, when the process data shows that the operating machine has not been serviced for a while but the material has recently been tested showing no problem, there is a high chance that the bad condition of the operating machine has caused the problem.

The relationship structure among chart patterns, process information, and assignable causes can are represented in Fig. 1. The chart patterns considered here which are among the most frequent patterns in control charts are discussed in Section 3.3.1. Meanwhile, the specific pieces of information from the process that are included in the network have been discussed in Section 3.3.2.

Bayesian networks are powerful tools for knowledge representation and inference under the uncertainty. The graphical nature of Bayesian networks allows seeing relationships among different variables and features. Using conditional independencies in the structure, they are able to perform probabilistic inference. They can not only learn from their mistakes but also they work with incomplete data. Such characteristics make Bayesian network a suitable candidate for modeling relationship structure in Fig. 1.

For this purpose, the rest of the paper is organized as follows: Section 2 reviews different techniques of RCA in the literature. Section 3 presents an introduction to Bayesian network, followed by detailed design of model and proposed data structure. Section 4 compares the proposed Bayesian network method with K-Nearest Neighbor (KNN) and Multi-Layer Perceptron (MLP), and discusses its performance under various conditions. Finally, Section 5 presents the conclusions and areas for future research.

2. Root cause analysis literature

There are a number of RCA methods in SPC, meanwhile there are other successful methods in other engineering fields mainly based on artificial intelligence techniques that are considered in this research. In this regard, Section 2.1 reviews the methods developed in SPC context. Next, Section 2.2 studies the methods from other engineering fields.

2.1. Root cause analysis techniques in SPC

Seder (1950a, 1950b) discusses the use of root causing diagrams in indentifying the assignable causes of out-of control conditions. Yang, He, and Xie (1994) use multivariate statistical methods

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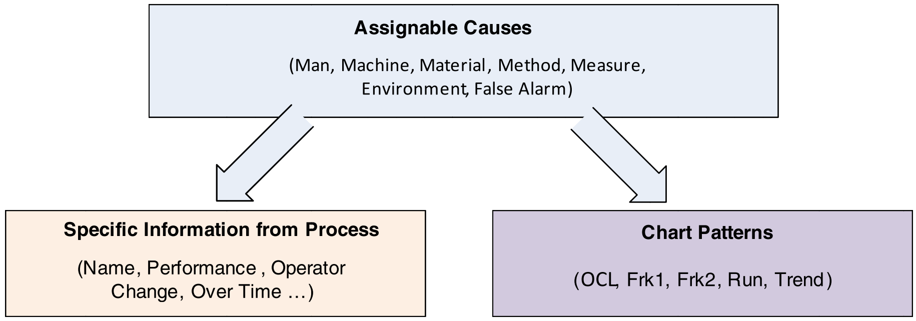

Fig. 1. Relationship among chart patterns, process information and possible root causes.

combined with engineering judgment to diagnose assignable causes. Doggetti (2005) provides a framework for analyzing the performance of three RCA tools: cause-and-effect diagram, interrelationship diagram, and reality tree. Their framework provides information on performance characteristics of the tools so that decision-makers can better understand the underlying assumptions of a recommended solution. Sarkar (2004) proposes a technique which is based on the analysis of the sequence of events preceding the out-of-control state to identify the most likely cause/s of failure. Pollock, Raymer, and Waters, 1998 discuss RCA procedure in practice. Bothe (2001) suggests the use of run charts to confirm root causes. Dew (1991) discusses three tools which are used in RCA including process diagram, barrier analysis, and change analysis. Montgomery (2005), Doty (1996) and Smith (2004) divide the assignable causes into six categories of Man, Machine, Method, Materials, Measure, and Environment. They suggest employing control chart patterns to determine one or more of above categories caused the out-of-control situation. Demirli and Vijayakumar (2008) develop a fuzzy rule based system for $\overline{X}$ hart, based on control patterns-cause relationship network, to resolve the uncertainties in identifying the (real) chart patterns and relating them to assignable causes. They also discuss that categorizing the out of control states into isolated shifts, sustained shifts and gradual shifts can hasten the RCA process.

2.2. Other root cause analysis techniques

Dassau and Lewin (2006) use optimization as a mean of automating RCA. They formulate the problem as a mixed-integer nonlinear program, whose system variables include the possible perturbations that affect low quality and low yield, with possible process improvements as decision variables. Weidl, Madsen, and Israelson (2005) develop a methodology that integrates decision-theoretic troubleshooting with risk assessment for industrial process control. They model the process using generic object-oriented Bayesian networks. Their system presents corrective actions with explanations of the root causes. Motschman and Moore (1999) discuss the process of RCA as well as corrective action in transfusion medicine. Dhafr, Ahmad, Burgess, and Canagassababady (2006) develop a methodology for identifying various sources of quality defects on the product. Leonhardt and Ayoubi (1997) present a summary of methods that can be applied to automatic fault diagnosis with a focus on classification and fuzzy based techniques. Mo, Lee, Nam, Yoon, and Yoon (1997) suggest a methodology based on clustered symptom tree which utilizes the advantage of the signed digraphs to represent the causal relationship between process variables and/or the propagation paths of faults in a simple and graphical way. Ge, Du, Zhang, and Xu (2004) use Hidden Markov Models for metal stamping process monitoring and fault diagnosis. They use a number of autoregressive models to model the monitoring signal in different time periods of a stamping operation and uses the residues as the features. Then, they employ a Hidden Markov Model (HMM) for classification. Widodo and Yang (2007) present a survey of machine condition monitoring and fault diagnosis using support vector machine. Lunze and Schiller (1999) provide an example of fault diagnosis by means of probabilistic logic reasoning. Dey and Stori (2005) use data from multiple sensors on sequential machining operations through a causal belief network framework to provide a probabilistic diagnosis of the root cause of the process variation. Chang and Ho (1999) apply neural network monitoring techniques to process control in an integrated monitoring/diagnosis scheme. The proposed technique contains a modified cause/effect diagram including process and part information which speeds up the diagnosis process.

3. Proposed Bayesian network

This section discusses the design process of the proposed Bayesian network. For this purpose, Section 3.1 provides an introduction to Bayesian network as a general framework for next sections. Section 3.2 discusses the detail structure of the proposed network. Finally Section 3.3 explains the data structure of the proposed method.

3.1. General structure of Bayesian network

Bayesian network, $B = \langle G, \Theta \rangle$, is a directed acyclic graph G that encodes a joint distribution over set of random variables $\mathbf{U} = \{X_1, \ldots, X_n\}$ where each variable X_i can take values from a finite set with instantiation of each variable represented by small letters, $\{x_1, \ldots, x_n\}$. The random variables are represented as vertices, and direct relationships between these random variables are represented as edges. Graph G encodes conditional independence, that is, each variable is independent of its non-descendents given the state of its parents. This conditional independence allows the modularity in the network in which complex system can be represented by consistent several modules. Therefore the statistical relations among variables can be represented by less number of parameters. The symbol Θ is used to represent the set of parameters that quantifies the network. The joint distribution of all variables in $\mathbf{U}$ defined by Bayesian network B as

$$P_B(\mathbf{U}) = \prod_{i=1}^{n} P_B\left(X_i \middle| \prod_{X_i}\right) \tag{1}$$

where $\prod_{X_i}$ denotes the set of parents of X_i in G. There is always a parameter $\theta_{x_i|\prod_{x_i}}$ for each possible value of x_i of X_i and its parent π_{x_i} of $\prod_{X_i}$. The symbol π_{x_i} denotes the state of any combination of parents of X_i. Therefore Eq. (1) can be written as $P_B(X_1, \ldots, X_n) = \prod_{i=1}^{n} \theta_{x_i|\pi_{x_i}}$. These conditional independencies allow performing inference in a reasonable amount of time. It is clear in formulation (1) that the lack of possible edges implies conditional