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An approach for developing diagnostic Bayesian network based on operation procedures

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ABSTRACT

In this paper, a novel approach of developing the Bayesian network for fault diagnosis based on operation procedures is presented. The proposed Bayesian network consists of operation procedure layer, fault layer and fault symptom layer. First, operation procedure layer containing procedure nodes and state decision nodes is developed. Second, the fault layer is determined based on the state decision nodes in the operation procedure layer. Then fault symptom layer including symptoms sensitive to the concerned faults is developed. Finally, the entire Bayesian network is established by integrating the three layers. The presented approach is applied to hydraulic control system of subsea blowout preventer (BOP). Taking an example of closing the BOP, the operation procedures are illustrated. The entire Bayesian network for fault diagnosis of closing the BOP is established. Several cases possible to appear during the closing process are studied to evaluate the developed model.

1. Introduction

Fault diagnosis and prognostics has obtained a lot of attention because the growing demands for safety and reliability of engineering systems. Bayesian networks are a powerful tool in knowledge representation and reasoning, suitable for the modeling of casual processes with uncertainty. A Bayesian network is an acyclic directed graph, consisting of nodes and arcs between the nodes (Pernestål, Nyberg, & Warnquist, 2012; Velikova, Van Scheltinga, Lucas, & Spaanderman, 2014). In the networks, nodes represent random variables and directed arcs define the probabilistic dependences between the variables (Marquez, Neil, & Fenton, 2010). The probabilistic dependences are quantified by a conditional probability table for each node (Arsene, Dumitrache, & Mihu, 2011). Each conditional probability table contains the probability of a node, given any possible combination of its parent nodes. Without parent nodes, root nodes only have priori probabilities. Given the values of the observed variables as evidences, the posterior probabilities of the unobserved variables could be obtained by inferences.

Recently, Bayesian networks for fault diagnosis have been widely used in various fields. Barco, Lázaro, Wille, Díez, and Patel (2009) present an automatic diagnosis system for the radio access network of wireless systems and experimental results have shown the feasibility of the proposed methods. Sahin, Yavuz, Arnavut, and Uluyol (2007) develop a fault diagnosis system for airplane engines using Bayesian network and distributed particle swarm optimization, which is used for learning the structure of the model form a large dataset. Riascos, Simoes, and Miyagi (2008) present a fault diagnosis system to diagnose different types of faults during the operation of a proton exchange membrane fuel cell based on the on-line monitoring of variables easy to measure in the machine such as voltage, electric current and temperature. Cruz-Ramírez, Acosta-Mesa, Carrillo-Calvet, Alonso Nava- Fernández, & Barrientos- Martínez, 2007 evaluate the effectiveness of seven Bayesian network classifiers as potential tools for the diagnosis of breast cancer using two real-world database and an average accuracy of 93.04% for the former and 83.31% for the latter are obtained. Alaeddini and Dogan (2011) develop a hybrid intelligent method based Bayesian networks for fault detection and diagnosis in control charts, which describes the cause and effect relationship among chart patterns, process information and possible root/assignable causes. Zhao, Xiao, and Wang (2013) propose a three-layer Bayesian network to simulate the actual diagnostic thinking of chiller experts and the developed model includes fault layer and fault symptom layer and additional information layer. Sun, Tang, Ding, Lv, and Cui (2011) develop a Mild Cognitive Impairment (MCI) expert system to address MCI's prediction and inference question to assist the diagnosis of doctor and the experimental results indicate that the developed model achieved better results than some existing methods in most instances. Verron,

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Tiplica, and Kobi (2010) present a methodology for industrial process diagnosis with Bayesian network and the performances of the method are evaluated on the data of an example.

The structure of Bayesian networks is a graphical and qualitative illustration of relationships among different nodes using directed arcs. There are two ways for establishing the structure of a Bayesian network. The first way is machine learning using data sets. Based on complete or incomplete data, many structure learning algorithms have been proposed (Gasse, Aussem, & Elghazel, 2014; Masegosa & Moral, 2013; Studený & Haws, 2014; Villanueva & Maciel, 2014). The second way is manually developed by experts. Generally, the experts develop the network based on the cause and effect relationship among the defined variables (Bouejla, Chaze, Guarnieri, & Napoli, 2014; Xiao, Zhao, Wen, & Wang, 2014). Within the scope of the second way for constructing Bayesian network, some researchers have proposed several approaches by using the existing models of the system. Bobbio, Portinale, Minichino, and Ciancamerla (2001) take advantage of the developed fault tree of the system to build the Bayesian network for fault diagnosis. Lo, Wong, and Rad (2011) propose a novel approach for constructing the Bayesian network structure based on a bond graph model. For the systems without fault trees or bond graphs, these approaches are inapplicable.

To achieve a specific function, several procedures are needed to perform in order and the following procedure depends on the previous one. Hence, state decision is needed to determine whether the previous procedure is completed successfully or not. So, fault diagnosis models can be established for state decision. This paper proposes a generic fault diagnosis method for constructing the Bayesian network structure based on the operation procedures. The proposed Bayesian network for diagnosis has three layers: operation procedure layer, fault layer and fault symptom layer. Based on the operation procedure layer, it is convenient to build one entire Bayesian network for fault diagnosis, which can be integrated by developing the diagnostic subsystems of state decisions. The operation procedure layer makes the diagnostic process more clear and organized. The reminder of this paper is organized as follows. Section 2 describes the proposed approach. In Section 3, a case study is presented to illustrate the implementation steps. Section 4 performs fault diagnosis based on the developed Bayesian networks. Section 5 summarizes the paper.

2. The proposed fault diagnosis methodology

Fig. 1 shows a generic framework of structuring Bayesian network for fault diagnosis based on operation procedures. The proposed methodology consists of three layers: operation procedure layer, fault layer and fault symptom layer. The operation procedure layer is developed based on the operation procedures, which perform a function of the system. To achieve a specific function, several procedures are needed to perform in order and the next procedure depends on the previous one. State decision is used to determine whether the previous one is completed successfully or not. Therefore, the developed operation procedure layer in Bayesian network is composed of procedure nodes and state decision nodes. Fault and fault symptom layers are developed based on the state decision nodes in operation procedure layer. Each state decision node is usually related with several faults. Through the operation procedure layer, all the faults leading to failures of a function can be connected together. Fault symptom layer includes sensor measurement information, which is sensitive to the faults. Usually several symptoms are used to identify the different faults.

The proposed methodology is a real-time fault diagnosis model in the process of performing a function. A fault detection system is needed for monitoring the important signals sensitive to the concerned faults. In addition, the diagnostic result is helpful to determine the next procedure to perform. For example, if a fault is diagnosed in the fault diagnosis system of "state decision A", the operation will move to procedure 3. If not, the operation will go on with procedure 2. To develop the structure of Bayesian network based on the proposed methodology, operation procedure layer is constructed firstly. Then the fault layer and fault symptom layer are developed according to the state decision nodes in the operation procedure layer. Finally, the entire Bayesian network is developed by integrating the operation procedure layer, fault layer and fault symptom layer.

A Bayesian network contains two elements, structure and parameters. After the development of Bayesian network structure, parameters for each node are needed to be determined. Root nodes have prior probabilities and child nodes have conditional probabilities based on the combination of their parent nodes. Prior probability of a node is the probability of the event occurs without new evidence or information. Conditional probability is the probability that an event occurs for the given new evidence. Generally, theses parameters can be defined by expert knowledge or learned from data sets (including faulty and normal data). The two methods can be used individual or jointly (Zhao et al., 2013).

3. Case study

3.1. Hydraulic control system of subsea blowout preventer

In this section, the proposed methodology is applied to hydraulic control system of subsea blowout preventer (BOP), the schematic diagram of which is shown in Fig. 2. For redundancy, a subsea BOP system has two identical control pods, blue pod and yellow pod. Each pod is able to perform all necessary functions on the BOP, containing solenoid valves and reducing valves. When the control system is in operation, one pod is active and the other one is standby. Once there is something wrong with the active pod, the standby one will replace it to continue working. In each pod, there are main control system and locking system. The main control system is responsible for opening or closing the ram of subsea BOP and the locking system is used for locking the ram when it is in position. Accumulators provide high and low pressure fluid to control BOP and lock the ram. An example of closing the subsea BOP is used to demonstrate the proposed approach.

Fault diagnosis is a reasoning process from symptoms to faults. Usually, it is not a fixed one-to-one correspondence between the faults and symptoms. One fault may lead to several different symptoms while one symptom may be caused by two or more faults. Therefore, it is more reasonable to give the probabilities of faults at given symptoms in the diagnostic results. A deterministic based model reports the diagnostic results in the Boolean format, i.e. Yes/Faulty. It does not consider the uncertainties when developing the model. However, uncertainties widely exist in sensors, faults, symptoms, fault-symptom relationships, the interconnection between a fault and other faults/symptoms (Huang, 2008; Xiao et al., 2014). For example, the collected diagnostic information for the same fault is not always the same every time due to sensor bias or observation error. In Bayesian network, the uncertainties are reflected by the probabilities (Philippot, Santosh, Belaid, & Belaid, 2014; Syu & Lang, 2000). Assuming $P(Symptom\ 1 = abnormal|Fault\ 1 = present) = 95\%$, it means that symptom 1 is very possible to be abnormal if fault 1 is present. The probability 95% takes into account of uncertain factors such as sensor accuracy, induced electrical noise, etc.