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Intelligent fault inference for rotating flexible rotors using Bayesian belief network

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ABSTRACT

Flexible rotor is a crucial mechanical component of a diverse range of rotating machineries and its condition monitoring and fault diagnosis are of particular importance to the modern industry. In this paper, Bayesian belief network (BBN) is applied to the fault inference for rotating flexible rotors with attempt to enhance the reasoning capacity under conditions of uncertainty. A generalized three-layer configuration of BBN for the fault inference of rotating machinery is developed by fully incorporating human experts' knowledge, machine faults and fault symptoms as well as machine running conditions. Compared with the Naive diagnosis network, the proposed topological structure of causalities takes account of more practical and complete diagnostic information in fault diagnosis. The network tallies well with the practical thinking of field experts in the whole processes of machine fault diagnosis. The applications of the proposed BBN network in the uncertainty inference of rotating flexible rotors show good agreements with our knowledge and practical experience of diagnosis.

1. Introduction

Flexible rotor has been widely used in a wide range of rotating machineries in the modern industry, such as centrifugal compressor, turbine generator, combustion and gas turbine. Therefore the fault diagnosis of flexible rotor plays an important role in the manufacture and maintenance of these machineries. With the rapid development of modern science and technology, rotating machinery is apt to develop with high rotary speed and high efficiency, which calls for more accurate, intelligent and efficient fault inference and diagnosis methods. In engineering, mechanical fault diagnosis is an inverse problem of the inherent causality of causes (faults) and effects (symptoms) and it is a complex inference process from machine symptoms to faults. In most cases, there is seldom fixed one-to-one correspondence between the symptoms and faults. One type of fault may lead to several typical symptoms while one symptom may also be caused by two or more faults. Moreover, the diagnostic information collected sometimes is incomplete because of the limited on-site conditions (e.g. online measurement condition). Consequently, the fault diagnosis has often to be conducted under uncertainty or incomplete information. This phenomenon is particularly true for rotating flexible rotors because of the complex corresponding relationships between the symptoms and faults and the difficulties in measuring and collecting useful signals for diagnosis.

Fault diagnosis of mechanical or electronic components or systems is a subject of expert system applications. Recently, continuous attempts have been made to develop intelligent expert approaches for fault diagnosis using artificial intelligence. The notable models include artificial neural network (Demetgul, Tansel, & Taskin, 2009; Wu & Kuo, 2009), Fuzzy Sets Theory and Inference (Saravanan, Cholairajan, & Ramachandran, 2009; Shen, Tay, Qu, & Shen, 2000), support vector machine (Widodo, Yang, & Han, 2007; Xian & Zeng, 2009; Zhang, Liu, Xie, & Li, 2009), Genetic Algorithms and Programming (Wang, Tseng, Chen, & Chao, 2009; Zhang & Nandi, 2007) and the hybrids of these methods (Fei & Zhang, 2009; Geng & Zhu, 2009; Samanta, Al-Balushi, & Al-Araimi, 2003; Tran, Yang, Oh, & Tan, 2009). For instance, Wu and Kuo (2009) have developed a fault diagnosis system for automotive generators using an artificial neural network (ANN). In this system, the features of the generator signals at different engine speeds and faults were extracted by using discrete wavelet transform. Then the back-propagation neural network (BPNN) and the generalized regression neural network (GRNN) were used to classify the synthetic fault types. For the diagnosis and inference of valve fault in a multi-cylinder diesel engine, rough sets theory was used to extract the useful rules by analyzing the decision table composed of attributes extracted from the vibration signals (Shen et al., 2000). These extracted rules were proven to be effective in distinguishing the fault type and inspecting the dynamic characteristics of the machinery. Xian and Zeng (2009) have conducted the intelligent fault diagnosis of the rotating machinery by using a hybrid support vector machine (SVM). The faulty vibration signals were first decomposed by the wavelet packet analysis. Then the

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extracted features were analyzed by the hybrid SVM for estimating fault types. Compared to conventional back-propagation network, the superiority of the hybrid SVM method was shown in the success of fault diagnosis. Zhang and Nandi (2007) have also proposed the genetic programming (GP) schemes for solving multi-class classification problems in roller bearing fault detection. The classification results were compared with two genetic algorithm (GA) based approaches GA/ANN and GA/SVM. Experiments showed that the proposed bundled-GP scheme was strong in feature selection and was equivalent to or outperformed the two GA-based approaches. In the integration of fuzzy logic and neural network algorithm, Tran et al. (2009) developed a method for fault diagnosis of induction motors based on the adaptive neuro-fuzzy inference system. In this method, two consecutive steps were involved. A decision tree was first used as a feature selection procedure to select valuable features from data set. Then, the neuro-fuzzy inference system was used to diagnose the faults of induction motors.

Though the above valuable models enabled the fault inference and diagnosis of mechanical or electronic systems, they tend to rely on data signals from sensors and thus are not sufficiently robust to the uncertainty and incomplete diagnostic information collected. Therefore the development of a new type of expert system, which fully tallies with the diagnostic thinking of human experts, and is powerful in handling uncertainty and flexible in acquisition of diagnostic knowledge, is necessary for the intelligent fault diagnosis of rotating flexible rotors.

In this paper, an intelligent expert system based on Bayesian belief network is developed by making full use of human experts' knowledge, machine faults and fault symptoms as well as machine running conditions. Considering the characteristics of rotating machinery, a generalized three-layer configuration of BBN is developed. The proposed topological of causalities takes account of more practical and complete diagnostic information as compared to the Naive diagnosis network. The remainder of this paper is organized as follows. The fundamental theory of Bayesian belief network, including Bayesian theorem, network topological, independence assumption and inference algorithms, is briefly introduced in Section 2. Section 3 presents a generalized three-layer configuration of BBN for the fault diagnosis of rotating machineries. In Section 4, the proposed network is applied in the fault diagnosis and uncertain inference of rotating flexible rotors. Afterward, the conclusion remarks are drawn in Section 5.

2. Bayesian belief network (BBN)

Bayesian belief network, or Bayesian network, is a kind of probabilistic inference network. It represents graphically a set of nodes (random variables) connected by directional arrows that quantify the causal relationship between the nodes (Barrientos1 & Vargas, 1998; Pearl, 1988). Bayesian network techniques provide a powerful tool for knowledge representation and reasoning under conditions of uncertainty. This theory has been developed and used in many areas, such as quality evaluation (Correa, Bielza, & Pamies-Teixeira, 2009), dynamic analysis (Barrientos1 & Vargas, 1998), cost-benefit analysis (Lu, Bai, & Zhang, 2009), risk management (Lee, Park, & Shin, 2009), aeronautic and medical diagnosis (Charles, Linda, Katherine, & Peter, 1997; Dey & Stori, 2005; Riascos, Simoes, & Miyagi, 2007; Sahin, Yavuz, Arnavut, & Uluyol, 2007), as well as condition monitoring (Weidl, Madsen, & Israelson, 2005).

In recent years, with the development of large-scale database system, Bayesian network has become a popular knowledge representation scheme for probabilistic knowledge in data mining (Heckerman, 1997; Jaroszewicz, Scheffer, & Simovici, 2009) and knowledge discovery (Lee & Abbott, 2003), and it has become a powerful tool for decision support (Lauria & Duchessi, 2006). Bayesian networks have shown superior performance as compared to neural networks, support vector machines, decision trees, and so forth, for several high-level classification tasks such as data mining, fault monitoring, bioinformatics, and so forth (Mittal & Kassim, 2007).

2.1. Bayesian theorem and inference

Supposing A and B are two random events and $P(B) > 0$, the probability of event A given the event B is called conditional probability and it can be written as:

$$P(A|B) = \frac{P(AB)}{P(B)} \tag{1}$$

in which $P(AB)$ is called the joint probability and $P(AB) = P(B)P(A|B) = P(A)P(B|A)$.

Furthermore, supposing $B_1, B_2, \ldots, B_n$ are a set of random variables and satisfy: (a) $\sum_{i=1}^{n} B_i = S$ where S is the certain event; (b) they are mutually exclusive; and (c) $P(B_i) > 0$, $i = 1, 2, \ldots, n$, for any given event A, we have the following marginal probability:

$$P(A) = \sum_{i=1}^{n} P(B_i)P(A|B_i). \tag{2}$$

Therefore, Bayesian theorem can be obtained by the above condition probability and marginal probability:

$$P(B_i|A) = \frac{P(AB_i)}{P(A)} = \frac{P(B_i)P(A|B_i)}{\sum_{i=1}^{n} P(B_i)P(A|B_i)}. \tag{3}$$

If all items on the right hand side are called prior probabilities and the item on the left is called the posterior probability, Bayesian theorem actually provides a calculation method of posterior probability from prior probabilities. The simple Bayesian inference or diagnosis is just based on this calculation for reasoning. For instance, the prior probability of a particular fault B_i and the prior conditional probability of symptom A given the fault can be estimated, and thus we can compute the probability $P(B_i|A)$ of fault B_i given the symptom A.

The above case is relatively simple. If the case involves a large number of events, the computation will be complicated and the required prior probabilities will be exponentially expanded. Therefore, the simple Bayesian diagnosis is impractically to apply. Bayesian network alternatively provides a feasible methodology for handling the difficulties. This network first enables a concise description of affairs and their complex relationships, and then based on the assumption of independence, significantly reduces the prior probabilities required in reasoning.

2.2. Topological of Bayesian network

Bayesian networks are graphs composed of nodes and directional arrows. Nodes in BBN represent random variables and directional arrows between pairs of nodes indicate the causal relationships or probabilistic dependence between the linked variables. The nodes can have two or more states, and for each node, every other node that has a direct influence on it is called a parent of this node. The strength of relationships between the variables is expressed as conditional probability that represents the conditional probabilities of a node given the set of its immediate parents. Fig. 1 shows a simple Bayesian network. The nodes without any input arrow or predecessor are called root nodes, such as X_1 and X_2. X_3 and X_4 are the immediate parent nodes of X_5 while they are also the child nodes of X_2.