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Bond graph based Bayesian network for fault diagnosis

C.H. Lo[a], Y.K. Wong[b,*], A.B. Rad[c]

[a] Division of Science, Technology, HKCC, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong, China
[b] Department of Electrical Engineering, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong, China
[c] School of Engineering Science, Simon Fraser University, 250-23450, 102nd Avenue, Surrey, BC V3T 0A3, Canada

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ABSTRACT

Model-based fault diagnosis using artificial intelligence techniques often deals with uncertain knowledge and incomplete information. Probability reasoning is a method to deal with uncertain or incomplete information, and Bayesian network is a tool that brings it into the real world application. A novel approach for constructing the Bayesian network structure on the basis of a bond graph model is proposed. Specification of prior and conditional probability distributions (CPDs) for the Bayesian network can be completed by expert knowledge and learning from historical data. The resulting Bayesian network is then applied for diagnosing faulty components from physical systems. The performance of the proposed fault diagnosis scheme based on bond graph derived Bayesian network is demonstrated through simulation studies.

1. Introduction

The growing demand for safety and reliability of modern engineering systems motivate the development of robust fault diagnosis algorithm. Early approaches, such as, fault tree analysis, expert systems, to fault diagnosis are inherently rule-based. They are proved to be inflexible, incomplete, and required comprehensive a prior knowledge of the fault characteristics, rather than actually deducing the fault themselves. Most advanced fault diagnosis algorithms now concern of using model that is derived from system's structure and behavior in order to establish the cause of system malfunction. This model-based fault diagnosis [1,8,11] enables more complex cause–effect reasoning and hence a more robust diagnostic system can be developed.

A number of different model-based fault diagnosis algorithms have been proposed in the past decades, capable of dealing with different diagnostic problems. Quantitative and qualitative are the two major approaches to model-based fault diagnosis. In quantitative fault diagnosis, precise mathematical model is used to monitor system states, detect abnormal behaviors and diagnose the failures. The main problems with such methodologies are the intricacy and overheads of obtaining precise numerical models and the sensitivity of the diagnostic system to modeling error. Usually, the effects of modeling errors obscure the effects of faults and cause false alarms [7,11]. Qualitative fault diagnosis which dominates in the AI community, without the use of precise numerical model and capable of dealing incomplete information, alleviate some problems encountered by quantitative approach. However, the lack of precision in the representation, and ambiguities introduced during the inference process, limit the application of the qualitative approach to complex systems [3].

Fault diagnosis based on AI techniques often deals with uncertain knowledge and incomplete input data. Probability reasoning is a method to deal with uncertain information, and Bayesian network is a tool that brings it into the real world applications [12–14]. In this paper, we proposed an alternative approach to model-based fault diagnosis, where Bayesian network is adopted to model the system and diagnose faulty system components. Bayesian network is a directed, acyclic graph (DAG), which embeds cause–effect relationship between variables (nodes). The representation framework of Bayesian network allows reasoning under uncertainty. Component failure probability of a system is computed by sequential evidence-propagation inference among conditional probability distributions that have been specified at each variable (node) [2].

The goal of the model-based fault diagnosis is to detect and localize faulty components in a system. Hence, the model used should incorporate structural information about the system and bond graph is such a representation. In this paper, a general procedure for constructing a Bayesian network structure on the basis of a bond graph model is proposed. Some researchers have proposed to learn the Bayesian network structure from data [4,9]. However, the accuracy of the learned Bayesian network is largely affected by the 'richness' of the data and the prior knowledge of the network ordering. There are several advantages of using bond graph model as

* Corresponding author.
E-mail address: eeykwong@polyu.edu.hk (Y.K. Wong).

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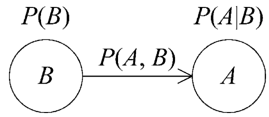

Fig. 1. A simple Bayesian network.

the skeleton to construct the Bayesian network for fault diagnosis. The task of identifying system variables to construct Bayesian network is completed and the localization of faulty components from Bayesian network is enhanced since they are already represented in the bond graph model. Bayesian network based fault diagnosis contributes to the possibility of ranking possible failures, handling multiple simultaneous failures and uncertainty symptoms of certain faults.

The paper is organized as follows. In Section 2, fundamental knowledge of Bayesian network is provided. Section 3 describes the construction of Bayesian network on the basis of bond graph model. In Section 4, fault diagnostic scheme based on Bayesian network and its results are presented. Finally, the paper is concluded in Section 5.

2. Bayesian network

Bayesian network, also known as probability network or belief network [4], are well established as a representation of relations among a set of random variables that are connected by edges and given conditional probability distribution at each variable. Bayesian network is a directed, acyclic graph (DAG) where nodes represent random variables. Causal relations are represented as a directed edge between variables, leading from the cause variable to the effect variable. As shown in Fig. 1, an edge from B to A indicates that B causes A.

Conditional probability distribution (CPD) is specified at each node that has parents, while prior probability is specified at node that has no parents (the root node). As shown in Fig. 1, the CPDs of variables A and C, are $P(A|B)$ and $P(C|B)$, respectively; and the prior probability of B is $P(B)$. The edges in the Bayesian network represent the joint probability distribution of the connected variables. For example, the joint probability distribution for the edge (B, A) is $P(A, B)$ which represents the probability of joint event $A \wedge B$. The fundamental rule of probability calculus shown that,

$$P(A, B) = P(A|B) \cdot P(B), \tag{1}$$

and in general, the joint probability distribution for any Bayesian network, given nodes $\boldsymbol{X} = X_1, \ldots, X_n$, is,

$$P(X) = \prod_{i=1}^{n} P(X_i|parents(X_i)), \tag{2}$$

where $parents(X_i)$ is the parent set of node X_i. Eq. (2) is known as the chain rule, which indicates the joint probability distribution of all variables in the Bayesian network is the product of the probabilities of each variable given its parents' values.

Inference in the Bayesian network is the task of computing the probability of each variable when other variables' values are known. That means once some evidence about variables' states are asserted into the network, the effect of evidences will be propagated through the network and in every propagation the probabilities of adjacent nodes are updated. The situation is mathematically formalized as the Baye's theorem,

$$P(X|Y) = \frac{P(Y|X) \cdot P(X)}{P(Y)} \tag{3}$$

which represents the probability of node X given evidence Y. The term $P(X|Y)$ denotes the posterior probability of node X can be computed when the likelihood ($P(Y|X)$) and prior probability ($P(X)$) are known; and $P(Y)$ denotes a normalizing factor, which is determined as follow,

$$P(Y) = P(Y|X) \times P(X) + P(Y|\neg X) \cdot P(\neg X) \tag{4}$$

where $\neg X$ denotes the complement of variable X. In fault diagnosis application, variable X may be interpreted as the hypotheses of fault and evidence Y is the observed symptoms.

Fault diagnosis in a qualitative sense is the reasoning of the cause–effect or fault-symptom relations and in almost all cases single symptom will be caused by several faults, while single fault will exhibit several symptoms [6]. This is also the case in the medical diagnosis. In this situation, Bayesian network provides an alternative approach to tackle the diagnosis problem. Every faults and symptoms are modeled by random variables in the network with a probability distribution. When observed symptoms (evidences) are input to the network, probabilities of every fault are computed according to the Baye's rule, Eq. (3). So, ranking of different faults with the given symptoms is possible and the possibility of eliminating possible fault candidates as in the case of qualitative reasoning is reduced.

3. Building model

The performance of model-based fault diagnosis will be greatly impaired when a poor model is used. The construction of Bayesian network by intuition may be inefficient. Recently, some researchers proposed to automate the construction process by learning the network structure through data [4,9]. However, the accuracy of the learned Bayesian network is largely affected by the 'richness' of the data and the prior knowledge of the network ordering. Moreover, when the number of variables in the network is increased, the learning algorithm rapidly becomes computationally infeasible and 'enormous' data is necessary [9]. To overcome this problem, bond graph model is proposed to generate the required Bayesian network. Before discussing this generation process, the basic procedures for constructing Bayesian network is presented.

3.1. Modeling elements

The construction of a Bayesian network consists of the following procedure

1. Identify hypothesis events and achievable information to the network and represent them into a set of random variables, such as, hypothesis variables and information variables, respectively.
2. Establish directed links between variables for a causal network. Mediating variables (neither hypothesis variables nor information variables) are often introduced to facilitate the acquisition of conditional probability distributions (CPDs), reflect independence properties in the domain, or other purposes [4].
3. Specify the CPDs at each variable.

The purpose of Bayesian network is to estimate certainties of events that are unobservable or costly to observe (i.e., hypothesis variables) when evidences (i.e., information variables) are given. The variables in Bayesian network may be discrete, having a finite number of states, or they may be continuous. Mediating variables are introduced in order to have a more refined network model of the domain. If the introduction of mediating variables serves no purpose, we should eliminate them from the model or they may menace performance as increasing the computational complexity [4]. Historical data and expert knowledge are employed to specify the conditional probabilities at each node. Fig. 2 shows the Bayesian network model constructed from the above procedures.