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Missile Fault Diagnosis Using a Learning Bayesian Network

Aruna Gunda, Varsha Teratipally

Department Of Computer Science And Engineering, University College Of Engineering,
Osmania University, Hyderabad, India

***Abstract* - This paper discusses the implementation of Missile fault diagnosis system based on a learning Bayesian network which is a part of "Expert System for Missile Diagnosis" project from ASL (Advanced Systems Laboratory), Defence Research and Development Organization, Hyderabad. Missile diagnosis involves a lot of uncertain and incomplete data. Probabilistic theory deals with such uncertain information and Bayesian network serves as an effective tool to implement Probabilistic theory for real-time applications. In this paper, we demonstrate how a learning Bayesian network can be used for missile diagnosis.**

***Index Terms* - Fault diagnosis, missile, Bayesian network, learning, probabilistic theory**

I. INTRODUCTION

Missile fault diagnosis has always been a challenge with ever-changing requirements and ever-increasing requirements for accurate diagnosis. In order to incorporate such requirements, a system based on learning provides an effective solution. Our diagnosis system uses WiseNet and a learning Bayesian network to resolve uncertainty and infer probable faults. The rest of the paper discusses the structure of our expert system and gives an insight into the concrete implementation of the application.

II. BAYESIAN EXPERT SYSTEM

User queries act as primary evidence for diagnosis in the fault diagnosis system.The input query is tokenized into a sequence of words and is matched with WiseNet. WiseNet is a large and structured set of texts. They are used for statistical analysis and hypothesis testing, checking occurrences or validating linguistic rules within a specific language territory. WiseNet is the main knowledge base. It consists of the words related to the domain and possible interpretations of the words (synonyms).

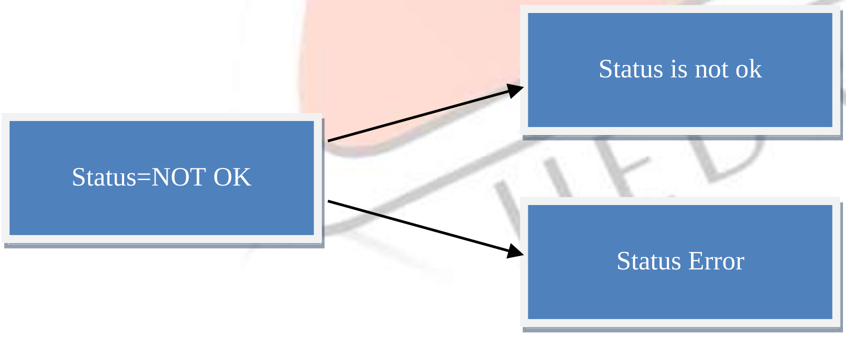

Figure 1.1 Possible interpretations of the fact

When a query is entered, the words are searched with words in WiseNet. If the word doesn't match with those in the WiseNet, then it is rejected. Otherwise, a Bayesian network is used to estimate the probability for every cause and learn from the results.

Bayesian Belief Network represents variables as nodes linked in a directed graph as in a cause/effect model. Conditional probabilities are specified for every node and root causes have "a priori" probability. Run time calculation generates probability estimates for every node and this probability changes when any node receives a newly observed value. Thus, the Bayesian network performs both prediction and diagnosis based on simpler causal models.

Calculating weights of the Bayesian network nodes

Weights of the nodes are calculated as the ratio of the frequency of the node to the total frequency of the nodes.

$$weight = \frac{n}{N}$$

Where n is the frequency of the node
And N is the total frequency
The conditional probabilities are then calculated using Bayes' theorem

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

The joint probability function is

$$P(A, B, C) = P(A|B, C)P(B|C)P(C)$$

Query template

The input query is converted into template structure as below.

Prefix	Fact	Suffix

Figure 1.2 Template Structure

The system extracts required values from this template, infers the faults based on parameters and updates the values after inference so that the system can learn from the results. The query results are stored in query history database with the fact as an index.

III. IMPLEMENTATION

Initially, query history database is empty. After the query is converted into template structure, the system checks for any matches in the query history database. Below are the various possible results and system behavior in each case:

A .No Match

In this case, the query is presented to the query analyzer with the beliefs extracted from the query. The query analyzer analyzes evidence from the previous reports and the belief in the present case, predicts the solution and presents to the user.
E.g. For query "command input voltage is not sufficient", template structure would be

	command input voltage	is not sufficient

The system searches the query history database. As there is no match with any of the entries, the belief is presented to the query analyzer for prediction.

B. Single Match

In this case, the result is directly presented to the user.
E.g. For query "problem in the current drawn", the template structure would be

Problem	Current drawn	

The system searches the database for similar queries. For example, if it is matched with one entry i.e., "Problem with current drawn", the corresponding action "Replace MIU II" is presented to the user. If the user is not satisfied, it is passed to the query analyzer and the new result will be added to the database.

C. More than one Match

In this case, the query is presented to the query analyzer along with the matched query results. The query analyzer constructs a local Bayesian network with the result nodes.
E.g. For query, "status not ok", the template structure would be

	Status	Not ok

For example, there are two entries in the database which matches with the query structure, i.e., there is an uncertainty in this case. The uncertainty is resolved using Bayesian network by constructing a local Bayesian network with "replace OBC", "replace MIUIII" nodes and their parent nodes. Conditional probability is calculated for each node and the most probable fault is inferred using Junction tree algorithm and parameter learning as discussed in section IV. The results from inference are then updated to the query history database for learning.

The query history database looks like the following table

Prefix	Command/ Phrase/ Fact	Suffix	Action
	Status	Not Ok	Replace OBC
	Status	Not Ok	Replace MIUII
Problem with	Current drawn		Replace MIUII
	Status input voltage at MIUII	Is not Ok	Replace MIUII
Problem with	Connectivity between OBC and PLPSSU		Replace OBC

Figure1.5. Query History Database

IV. FAULT INFERENCE

The evidence is entered into the system based on the state information and then the Bayesian network nodes are updated with the calculated probabilities to reflect the new information. There are many different algorithms to perform inference task in Bayesian networks, which apply different tradeoffs between speed, complexity, generality, and accuracy. Variable elimination algorithm permits inference on a Bayesian network with a generic structure. Our diagnosis system implements a variable elimination algorithm- Junction Algorithm. Junction algorithm generalizes variable elimination by compiling the density into a data structure that supports the simultaneous execution of large class of queries. The algorithms take the form of message passing on a graph called a junction tree, whose nodes are clusters or sets of variables.

Junction tree algorithm

Given, each cluster C and each separator S a potential function over its variables.

Initialize $\phi_C(u) = \psi_C(u), \ \phi_S(u) = 1$

To pass a message from B to C over separator S, update

$$\phi_S^*(u) = \sum_{v \in X_{B \setminus S}} \phi_B(u \cup v), \ \phi_C^*(u) = \frac{\phi_C(u)\,\phi_S^*(u_S)}{\phi_S(u_S)}$$

After all the messages have been passed, $\phi_C \propto P_C$ for all clusters C.

Parameter learning

In order to reflect the changes after the query has been processed, the weights of cluster of nodes affected by the evidence are updated by a factor of $\frac{1}{n}$, where n is the total number of nodes

After each query is processed, the Bayesian network is dynamically updated to reflect the changes.

V. CONCLUSION

Construction of a learning Bayesian network for missile diagnosis is executed using probabilistic approaches. Fault records of some variables are constructed including variables. The record is essential for the construction of the network structure avoiding hidden variables. For diagnostic process (i.e. the inference), the evidence is based on observation of variables that can be easily monitored. This allows an easier and effective implementation of fault diagnosis in critical systems. Inference results from our fault diagnosis system and the original fault causes were in agreement with an accuracy of 76%.

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