Bayesian belief network based fault diagnosis in automotive electronic systems

Bayesian Belief Network Based Fault Diagnosis in Automotive Electronic Systems

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This paper presents an innovative diagnostic method tailored for automotive electronic system diagnostic tools. By incorporating a Bayesian Belief Network (BBN) technique, the proposed method is capable of guiding vehicle diagnostics in a probabilistic manner. In addition, the method features a multiple-DTC-orientated troubleshooting strategy, and is capable of giving an optimised procedure to simultaneously troubleshoot the failure cases with multiple DTCs logged. Moreover, an object oriented BBN structure has been employed to optimise the Bayesian diagnostic model. This strategy assigns a diagnostic model of a reasonable size and hence makes probability propagation feasible in practice.

Topics / Vehicle Diagnostics, Modeling and Simulation Technology

1. INTRODUCTION

With the growth in electrical/electronic content of automobiles, and the corresponding increase in product and engineering complexity, fault diagnostics are increasingly important for vehicle safety and reliability. Modern vehicles contain a number of electronic control units (ECUs), and these ECUs are able to store diagnostic trouble codes (DTCs) if certain problems occur in the vehicle. However, a stored trouble code does not always pinpoint the cause of the problem. One major problem for existing diagnostic methods is the successful interpretation of these DTCs logged from a faulty vehicle to correctly diagnose the most likely root cause.

Traditional troubleshooting flow diagrams are employed in the existing diagnostic tools for this purpose. This method is based on rule-based reasoning, and is suitable for domains that are "black and white", but not well suited to domains that are fuzzy or have a significant percentage of exception and uncertain cases. An automobile system features a huge complexity with multiple components and subsystems that interact with each other in complicated ways. Therefore, the knowledge acquired for the diagnostics can be uncertain and incomplete. In this circumstance, the diagnostics is not always well served by rule-based reasoning. One of the embodiments is that a diagnostic tool is prone to misdiagnosis if any of the nodes in the decision tree is skipped over or ignored.

In addition, it is common place to have multiple diagnostic trouble codes (DTCs) reported for a single fault. However, the troubleshooting flow diagrams are single DTC-oriented. This working mechanism does not allow all logged DTCs to be considered in an integrated manner, resulting in a number of unnecessary or ineffective tests and checks. A sensible diagnostic method should be able to simultaneously troubleshoot the multiple DTCs in an integrated way.

A Bayesian Belief Network (BBN) is a kind of expert model, and therefore suitable for knowledge-based diagnostic systems. Furthermore, BBN is designed for modeling and reasoning about uncertainty, and therefore suitable for troubleshooting complex automotive systems. This paper presents an innovative diagnostic method tailored for automotive electronic system diagnostic tools. By incorporating a BBN technique, the proposed method is capable of guiding vehicle diagnostics in a probabilistic manner, thereby emulating the human way of thinking. Moreover, the method features a multiple-DTC-orientated troubleshooting strategy, and is capable of giving an optimised procedure to simultaneously troubleshoot the failure cases with multiple DTCs logged, thereby leading to a more sensible and effective diagnosis.

A great deal of research has been conducted in medical diagnostics using BBN techniques [1, 2]. BBN has also been applied in the monitoring of manufacturing process [3, 4]. In contrast with an automobile system, these applications targeted a relatively specific and small system. For knowledge-based vehicle diagnostics, relevant research work has been reported by Foran and Jackman [5], who proposed a rule-based reasoning method for diagnosing distributed multi-ECU control systems. Gelgele and Wang [6] reported an expert system for engine fault diagnosis. Neil *et al.* applied a BNN to predict the reliability of military vehicles [7], and proposed a generic procedure on building large-scale Bayesian networks [8].

In addition, due to the increased complexity of the modern automobile, the fault information to be interpreted is massive, that is, a vehicle may contain tens of ECUs and one single ECU may contain more than one hundred DTCs. The main challenge of the research reported in this paper was in the structuring and optimisation of the Bayesian diagnostic model. An object oriented BBN structure has been proposed for this purpose. This strategy assigns a diagnostic model of a reasonable size and hence makes BBN propagation feasible in practice.

2. METHOD

2.1 Theory of Bayesian Belief Network

A Bayesian Belief Network is a probability-based graphic model, reflecting the states of a system that is being modelled and indicating how those states are related by probabilities. The key feature of a BBN is that it enables us to model and reason about uncertainty. Its strengths are ideally suited for diagnosing real world problems where uncertain incomplete data exists. The underlying theory of BBN was inspired from Bayes' Theorem, which states that

$$P(B \mid A) = \frac{P(BA)}{P(A)} = \frac{P(A \mid B)P(B)}{P(A)} \qquad (1)$$

where, for the application considered in this paper, the event A is the fault symptom and the event B is the fault cause generating A. $P(B|A)$ is the *posterior* probability that B is true, given that A is true; $P(B)$ is the *prior* probability that B is true; $P(A|B)$ is the *conditional* probability that A is true, given that B is true; and $P(BA)$ is the probability that both A and B are true. This can be considered as the simplest Bayesian Belief Network, containing only two nodes.

In practice, a BBN consists of a number of nodes, directed edges (links) and probability tables. Because the directed links are not allowed to form cycles, BBN is also called a directed acyclic graph. Nodes represent variables that can be failure symptoms, components and observations. Edges indicate casual relationships between the variables. The nodes are annotated with probabilities. For root nodes, these are prior probabilities. For other nodes, these are conditional probabilities that a given state of the node is present or absent, given that the parent nodes connected to it have failed or not. Conditional probabilities indicate the strength of causal relationship between the nodes.

The target of building a diagnostic BBN is to reversely infer the most likely cause, given one or more failure symptoms occur, i.e. to calculate posterior probabilities of the causes. The calculus of posterior probability involves calculating the joint probability for the model (probabilities of all combined states for all nodes within the model). To simply the calculus of the joint probability, BBN makes the following three assumptions of conditional independence:

1. All root nodes in the top layer of a network are independent of each other.
2. Any two unlinked nodes are independent, given the state of their common parent node.
3. A node is independent of their indirect parent (grandparent) nodes, given the states of all of its parent nodes.

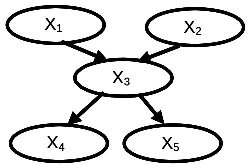

Fig 1 One example of a BBN

Fig. 1 gives an example of a BBN, which contains five nodes X_1, X_2, X_3, X_4, X_5 and with a structure of two layers. The following reasoning indicates how to calculate the posterior conditional probability $P(X_1{=}true|X_5{=}true)$ in virtue of the three types of conditional independence.

Bayes' Theorem (Eq. 1) gives

$$P(X_1 = true \mid X_5 = true) = \frac{P(X_1 = true, X_5 = true)}{P(X_5 = true)} \qquad (2)$$

where $P(X_1{=}true, X_5{=}true)$ and $P(X_5{=}true)$ are called marginal probabilities, and can be calculated from

$$P(X_1 = true, X_5 = true) = \sum_{X_2, X_3, X_4} P(X_1 = true, X_2, X_3, X_4, X_5 = true) \qquad (3)$$

and

$$P(X_5 = true) = \sum_{X_1 X_2 X_3 X_4} P(X_1, X_2, X_3, X_4, X_5 = true) \qquad (4)$$

where $P(X_1{=}true, X_2, X_3, X_4, X_5{=}true)$ and $P(X_1, X_2, X_3, X_4, X_5{=}true)$ involve calculating the joint probability of the model. In terms of the definition, the joint probability of this model $P(X_1, X_2, X_3, X_4, X_5)$ can be calculated from

$$\begin{aligned} P(X_1 X_2 X_3 X_4 X_5) &= P(X_1)\prod_{i=2}^{5} P(X_i \mid X_1 X_2 \ldots X_{i-1}) \\ &= P(X_1)P(X_2 \mid X_1)P(X_3 \mid X_1 X_2) \\ &\quad \times P(X_4 \mid X_1 X_2 X_3)P(X_5 \mid X_1 X_2 X_3 X_4) \end{aligned} \qquad (5)$$

Applying the three types of conditional independence, we know that: X_1 is independent of X_2; X_4 is independent of X_1 and X_2; and X_5 is independent of X_4, X_1 and X_2. Eq. 5 can then be simplified to give

$$\begin{aligned} P(X_1 X_2 X_3 X_4 X_5) &= P(X_1)P(X_2) \\ &\quad \times P(X_3 \mid X_1 X_2)P(X_4 \mid X_3)P(X_5 \mid X_3) \end{aligned} \qquad (6)$$

Substituting Eq. 6 into Eq. 3 and Eq. 4 makes the calculus of posterior probability much easier.

Apart from the three assumptions of conditional independence, the junction tree method is adapted to make the propagation of the BBN feasible. This method compiles the diagram into a junction tree of cliques, to localise computation to those nodes that are directly related.

2.2 Object Oriented BBN Structure

Bayesian Belief Networks are a NP-hard problem where computation grows exponentially with system complexity *i.e.* the size of the network. A modern automobile system normally contains tens of ECUs, and each ECU may contain more than 100 DTCs. It is impractical to model an automobile system using a single BBN model. Therefore, appropriate methods must be created to optimise the network structure and to achieve computational efficiency. A reasonable approximation based on causal independence has been proposed by Heckerman *et al.* [9] to alleviate the computational burden. Causal independence is the method of defining a discrete distribution that can dramatically reduce the number of prior probabilities necessary to define a distribution. In other work, Wang *et al.* [1] unburdened a BBN by optimally decomposing the network.

In this research, we employed an object oriented method for building a large scale Bayesian diagnostic model. The diagnostic boundary was defined as a single ECU, but can be extended into a complete vehicle system in virtue of the object oriented method. For the ECU, we generate one object oriented diagnostic model that contains all DTCs within the ECU, and integrates these DTCs in terms of the relationships between them. The method can be described as follows;

- An object oriented diagnostic model consists of one main BBN model and a number of BBN sub-models.
- The main BBN model gives an overview of the diagnostic models and indicates the relationships between the BBN sub-models.
- The BBN sub-models are constructed for individual components or component clusters grouped in terms of their functionality. These sub-models contain detailed diagnostic knowledge for diagnosing the specific components.
- A sub-model consists of multiple DTCs assigned to the component or component cluster and can be reused as a class.

For a failure case with multiple DTCs logged, if all logged DTCs belong to one sub-model, only this sub-model will be involved with probability propagation. If logged DTCs belong to multiple sub-models, all these related sub models will be involved with probability propagation via the main model. That is, the object oriented BBN structure does not make any influence on simultaneous diagnosis of multiple DTCs.

2.3. Knowledge Collection and Analysis

The following data sources were accessed for generating the diagnostic model: documentation such as subsystem specific diagnostic specifications (Part II), failure mode effect analysis (FMEA) and fault tree analysis (FTA); experience of diagnostic engineers; and field information such as warranty databases. Analysis of the documents generated a basic structure for the diagnostic models. A survey was conducted with the knowledge engineers to acquire the conditional probability values associated with the nodes in the diagnostic model. Statistical analysis on the historic warranty database was also performed to obtain prior probabilities for the root nodes.

3. CASE STUDY

An anti-lock brake system (ABS) has been used as a case study in this research. The electronic control unit for the ABS contains about 120 DTCs, which are assigned into a number of components. Fig. 2 shows the main Bayesian diagnostic model for this ECU. Each block in the main model represents a sub-model specified for a particular component or component cluster. Within each block, underlying nodes are hidden and only interface nodes can be viewed. These interface nodes consist of input nodes drawn with *dashed* borders and output nodes drawn with *solid* borders. The interface nodes are connected to other sub-models, and indicate the common causes between the connected sub-models. The ellipse nodes outside the blocks, such as hydraulic leakage and defective PC board, are common nodes for multiple components. From this figure, we can clearly see the causal relationship between the components.

The sub-model for the multi-axis acceleration sensor is shown in Fig. 3. There are five DTCs for this component, which are problem nodes. The others are cause nodes that are the possible causes for these DTCs. Each DTC may have its own specific causes, or may share some causes with other DTCs. The output nodes are drawn with *thick grey* borders while input nodes are drawn with *dashed thick grey* borders. It can be seen from Fig. 2 that the three output nodes are also connected to the yaw rate sensor. The three input nodes are linked to three common nodes, high fre/electric interferences, defective PC board and defective PCU. It should be noted that observation nodes can be also added into the model apart from the existing problem nodes and cause nodes. In addition, there is a conditional probability table for each node behind the model.

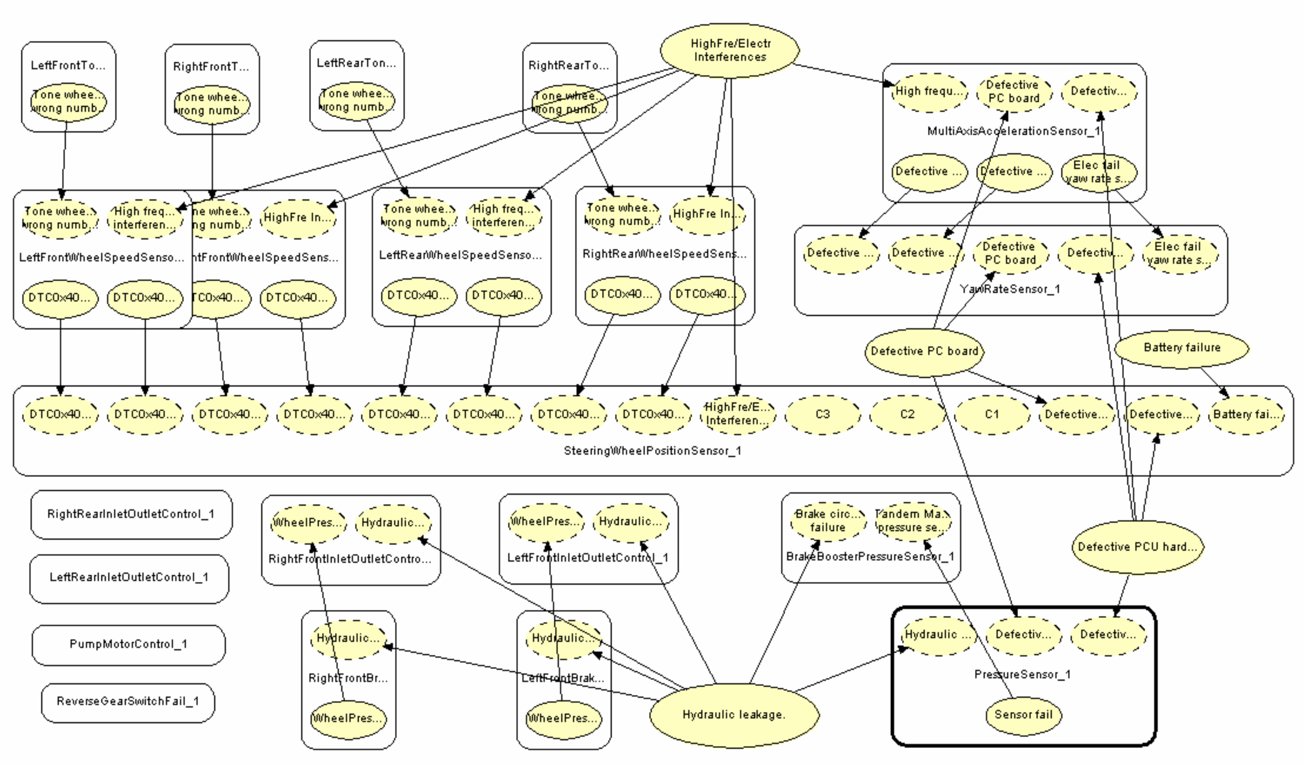

Fig. 2 Main Bayesian diagnostic model for an anti-lock brake system.

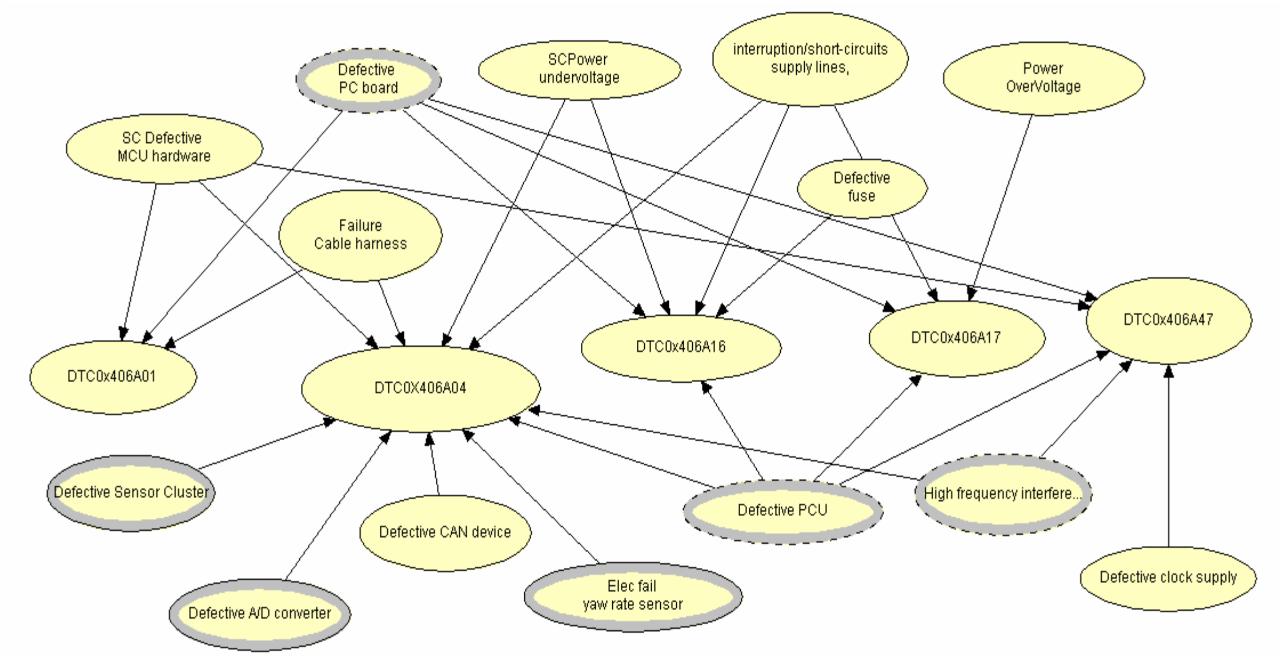

Fig. 3 Sub-model for multi-axis acceleration sensor.

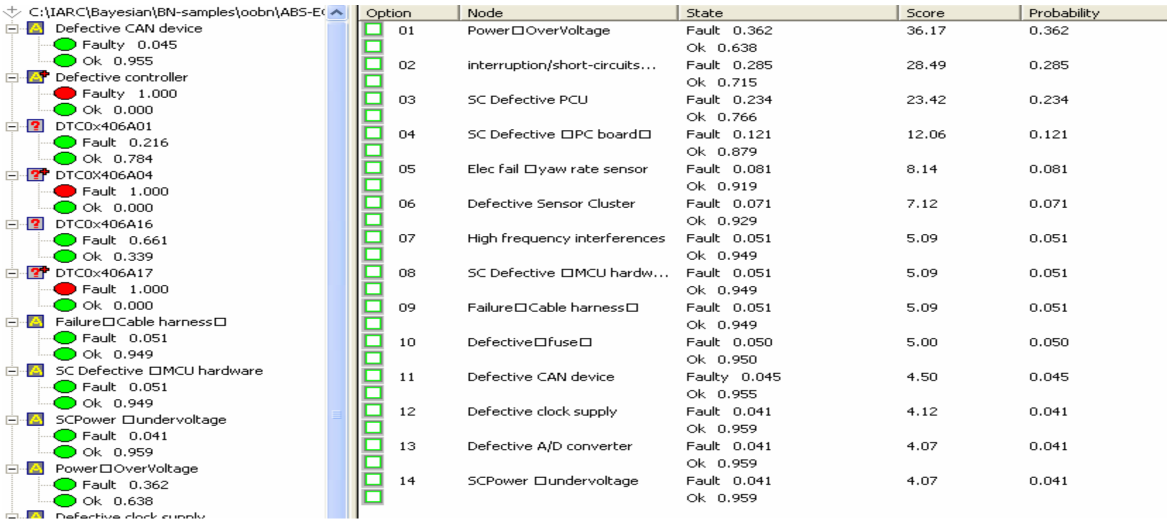

Fig. 4 Diagnostic procedure for a faulty case with three DTCs logged.

Fig. 4 indicates the diagnostic procedure for a fault case with three DTCs logged, *i.e*. DTC0x406A01, DTC0x406A04 and DTC0x 406A16. It can be seen from the node tree (left pane in Fig. 4) that three problem nodes were instantiated. The node tree also indicates the probabilities for all possible cause nodes. The right pane gives a troubleshooting action list ranked according to the probability of each possible cause node. As soon as an action (test, observation or repair) is taken, the corresponding node is instantiated with the result of the action. This causes the BBN to update the probabilities of the remaining nodes in terms of the new evidence so that a new action list is generated. The procedure is repeated until the failure has been repaired.

4. CONCLUSIONS

A Bayesian Belief Network based method has been developed for automotive electronic system diagnostics. In contrast to the traditional troubleshooting flow diagram, the method proposed possesses two distinctive advantages: (i) the method is able to guide diagnostics on a probabilistic basis; (ii) the method is capable of simultaneously diagnosing multi-DTCs in an optimised way. These two advantages make automotive electronic system diagnostics more effective and accurate.

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