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Probability based vehicle fault diagnosis: Bayesian network method

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Abstract Fault diagnostics are increasingly important for ensuring vehicle safety and reliability. One of the issues in vehicle fault diagnosis is the difficulty of successful interpretation of failure symptoms to correctly diagnose the real root cause. This paper presents an innovative Bayesian Network based method for guiding off-line vehicle fault diagnosis. By using a vehicle infotainment system as a case study, a number of Bayesian diagnostic models have been established for fault cases with single and multiple symptoms. Particular considerations are given to the design of the Bayesian model structure, determination of prior probabilities of root causes, and diagnostic procedure. In order to unburden the computation, an object oriented model structure has been adopted to prevent the model from overly large. It is shown that the proposed method is capable of guiding vehicle diagnostics in a probabilistic manner. Furthermore, the method features a multiple-symptoms-orientated troubleshooting strategy, and is capable of diagnosing multiple symptoms optimally and simultaneously.

Keywords Fault diagnosis · Bayesian belief network · Modelling · Automotive

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Introduction

With the increase in product and engineering complexity of automobiles, fault diagnostics are becoming increasingly important for vehicle safety and reliability. However, an automotive system is hard to diagnose because of two reasons. (1) An automotive system has a number of components and subsystems that interact with each other in complicated ways. (2) The possible root causes and the observations available to locate the real causes are numerous, leading to difficulty of successful interpretation of fault symptoms and observations. The task of troubleshooting is to interpret initial failure symptoms and derive a sequence of test to effectively and accurately allocate the real root causes of failures.

Conventional troubleshooting flow diagrams, also called fault trees, are widely employed to generate the test sequences for guiding the diagnostic technician. Figure 1 shows an example of a troubleshooting flow diagram for diagnosing a fault in a modern vehicle infotainment system. Initiated from the fault symptom, “SYS-NoSound”, this diagram guides the users to locate the defect by telling them which test to perform step by step. It seems this is exactly what the user needs. Actually, this method possesses several intrinsic drawbacks. (1) It is a kind of “if and then” reasoning, and troubleshooting decisions are made based on simple “yes” or “no” judgments. In practice, judgement on the failure cause can be uncertain; each troubleshooting step contains multiple uncertain options to be considered by the user. This means that the fault diagnosis should ideally be guided in a probabilistic way. (2) In each troubleshooting step, the user only has one fixed choice and is forced to perform the test suggested by the method. The user is prone to misdiagnosis if any of the tests in the diagram is problematic or skipped over. (3) The method has a rigid structure and does not allow the users freedom of choice in terms of their own diagnostic experiences and knowledge. (4) Each

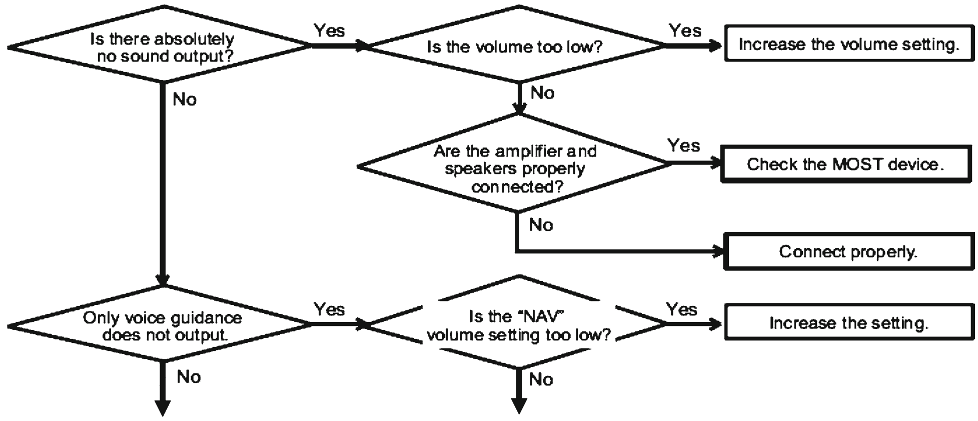


Fig. 1 A traditional troubleshooting flow diagram

troubleshooting diagram only deals with a fault case with a single symptom. For a fault case with multiple symptoms, which is common place, the method diagnoses the failures separately. This working mechanism does not allow all failures to be considered in an integrated manner, resulting in a number of unnecessary or ineffective tests and checks.

A Bayesian Belief Network (BBN) is a probability based modelling technique, and suitable for knowledge-based diagnostic systems. A BBN enables us to model and reason about uncertainty, ideally suited for diagnosing real world problems where uncertain incomplete data exist. Therefore, it is a suitable solution for troubleshooting complex automotive systems. This paper presents an innovative method for automotive fault diagnosis. By incorporating the BBN technique, the proposed method overcomes the drawbacks of conventional troubleshooting flow diagrams mentioned above. The advantages and novelty of the proposed method are; (1) It is probability-based method with the diagnostic decision made in terms of the probabilities of root causes. (2) It features a dynamic process where the probabilities in the model are constantly updated with respect to new evidences. (3) The method adopts a multiple-symptom-orientated troubleshooting strategy, and is capable of giving an optimised procedure to simultaneously troubleshoot a fault case with multiple symptoms.

In this study, a vehicle infotainment system has been selected as a case study. A number of diagnostic models have been established for fault cases with single symptom or with multiple symptoms. Particular considerations are given to the design of the model structure, determination of prior probabilities of root causes, and diagnostic procedure. In order to unburden the computation, an object oriented model structure has been adopted to prevent the model from overly large.

A great deal of research has been conducted in medical diagnostics using BBN techniques (Wang, Zheng, Good, King, & Chang, 1999; Kahn Jr, Roberts, Shaffer, & Haddawy, 1997). BBN has also been applied in the monitoring of manufacturing processes (Kang & Golay, 1999; Wolbrecht, D'Ambrosio, Paasch, & Kirby, 2000). 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 (2005), who proposed a rule-based reasoning method for diagnosing distributed multi-ECU control systems. Gelgele and Wang (1998) reported an expert system for engine fault diagnosis. Neil, Fenton, Forey and Harris (2001) and Neil, Fenton and Nielsen (2000) applied BNN to predict the reliability of military vehicles, and proposed a generic procedure on building large-scale Bayesian networks. The preliminary research results of this project have been also published in 8th International Symposium on Advanced Vehicle Control (Huang, Antory, Jones, & Groom, 2006).

This paper consists of four sections. "Bayesian belief network", following this introduction, gives generic analysis on the characteristics and probability calculation of a Bayesian Network. "Diagnosis for single symptom case" presents the Bayesian Network based method tailored for automotive diagnosis by using vehicle infotainment system as case study. Two types of models for single symptom fault case and multiple symptoms fault case have been discussed. "Diagnosis for multiple symptom case" presents the conclusions.

Bayesian belief network

Naïve Bayesian diagnostics

A naive Bayesian diagnostic model is a direct application of Bayes' theorem in engineering diagnostics. Figure 2 shows a basic structure of a naive Bayesian Network where A is a fault symptom and $B_i (i = 1, 2, \ldots n)$ are mutually exclusive and complete set of root causes generating A, Bayes' theorem gives the following relation between the symptom A and root causes B_i:

$$P(B_i|A) = \frac{P(B_i A)}{P(A)} = \frac{P(A|B_i)P(B_i)}{\sum_{i=1}^{n} P(B_i)P(A/B_i)} \quad (1)$$

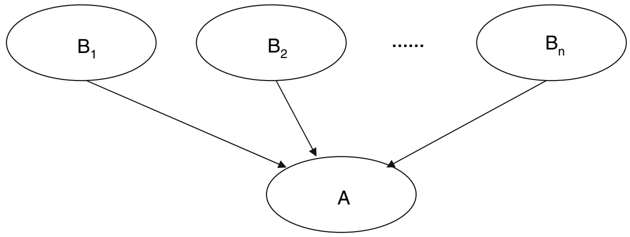


Fig. 2 A Navie Bayesian diagnostic model

If the prior probabilities $P(B_i)$ and prior conditional probabilities $P(A/B_i)$ that B_i generates A are known either from experience or statistical data, we will be able to calculate the posterior probability $P(B_i/A)$ that A is caused by B_i from Eq. 1. A Navie Bayesian diagnostics troubleshoots the fault by calculating the probability that the fault B_i occurs giving symptom A occurs, i.e. posterior conditional probability $P(B_i/A)$.

Two assumptions were made for Eq. 1 that the fault set $B_i(i = 1, 2, \ldots n)$ must be mutually exclusive and complete, i.e. the probabilities of B_i sum to unity. However, in vehicle fault diagnosis applications, fault set B_i is not exclusive and can occur simultaneously. Furthermore, it is very difficult to know complete root causes in practice. In addition, a practical diagnostic issue may be concerned with multiple layers of causal relationships, for example, each root cause may be indicated by different observations. Therefore, a naïve Bayesian diagnostic model is not a suitable solution for automotive fault diagnosis. As an extension of naïve Bayesian diagnostics, a BBN provides an effective solution for the issues addressed above.

Basic features of Bayesian belief network (BBN)

A Bayesian Belief Network is a probability-based graphic model that allows complex events to be described graphically as a network, and accordingly reason about the causal relationship between the events in a probabilistic manner. For a particular fault symptom, the BBN diagnostic model does not require a complete root cause set and accommodate the root causes occurring simultaneously.

Topology of the BBN

A BBN consists of a number of nodes, directed links and probability tables as shown in Fig. 3. Because the directed links are not allowed to form cycles, a BBN is also called a directed acyclic graph. For a BBN diagnostic model, nodes represent variables that can be failure symptoms, component defects (root causes) or observations. Directed links indicate casual relationships between the variables. The nodes are annotated with probabilities. For root edge nodes, these

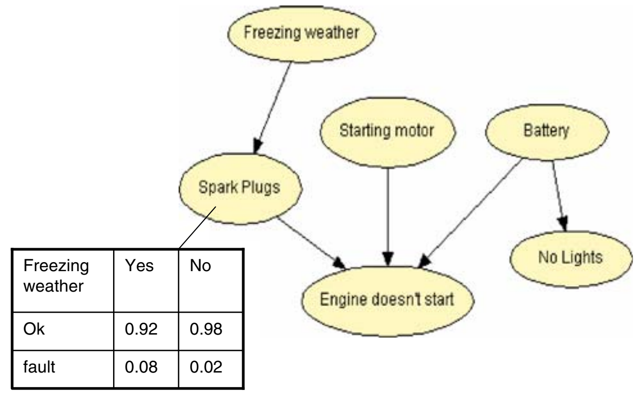


Fig. 3 A simple example of Bayesian network

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 relationships between the connected nodes.

Calculus of posterior conditional probability

The target of building a diagnostic BBN is to reversely infer the most likely root cause, given one or more failure symptoms occur, i.e. to calculate posterior probabilities of the cause. 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 simplify 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.

Figure 4 gives an example of a BBN illustrating these three types of conditional independence. The network contains five nodes X_1, X_2, X_3, X_4, X_5 with a structure of three layers. In terms of the definition of the three types of conditional independence, X_1, is independent of X_2, given the state of X_3 X_4 is independent of X_1 and X_2; and X_5 is independent of X_4, X_1 and X_2. The following derivation indicates how to calculate the posterior conditional probability $P(X_1 = \text{true}|X_5 = \text{true})$ in virtue of the three types of conditional independence. Bayes' Theorem gives

$$P(X_1 = \text{true}|X_5 = \text{true}) = \frac{P(X_1 = \text{true}, X_5 = \text{true})}{P(X_5 = \text{true})} \quad (2)$$

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

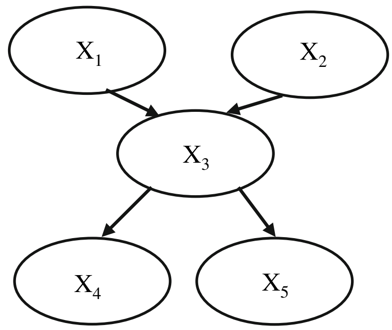


Fig. 4 Three types of conditional independence

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

and

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

where $P(X_1 = \text{true}, X_2, X_3, X_4, X_5 = \text{true})$ and $P(X_1, X_2, X_3, X_4, X_5 = \text{true})$ 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

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

Applying the three types of conditional independence, Eq. 5 can be simplified as

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

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

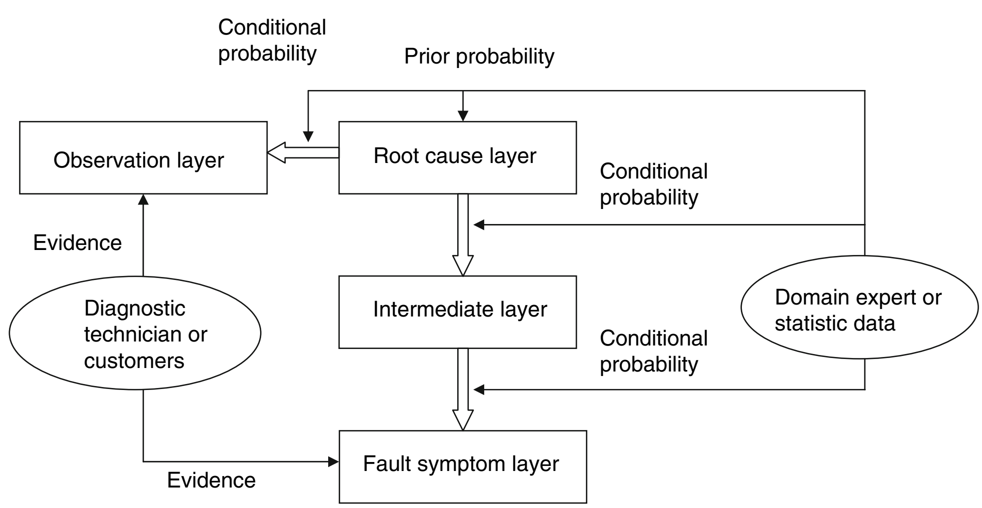
Diagnosis for single symptom case

A vehicle Infotainment system has been selected as an application case in this work. The diagnosis is symptom based, and the fault symptoms to be modelled were categorised in terms of subsystems, functions, operations by using four levels of qualifier. Such a typology of fault symptoms is also in line with the common quality data of the system supplier. The strategy was to establish a number of sub-models for diagnosing the fault case with a single symptom reported, and adopt an object oriented model structure to connect related sub-models for diagnosing the fault cases with multiple symptoms reported.

Framework of the single symptom diagnostic model

The existing troubleshooting flow diagrams are an important basis of building Bayesian diagnostic models. Figure 1 indicates that a troubleshooting flow diagram consists of two types of node, i.e. observation node wrapped by lozenges and action node wrapped by rectangles. In terms of these characteristics, we proposed a tailored structure of Bayesian diagnostic model as indicated in Fig. 5. The Bayesian diagnostic model contains four layers of events, i.e. fault symptom, intermediate, root cause and observation. There are direct causal relationships between the layers. The layer of fault symptom is the failure symptom reported by the customer such as “no display”, “no sound” or failure code logged

Fig. 5 Framework of the Bayesian diagnostic model



by the service technician such as diagnostic trouble codes (DTC). The layer of root cause consists of all possible root causes generating the fault symptoms such as faulty components, disconnected harness, and software problems. The layer of intermediate nodes is in between the fault symptom layer and the root cause layer. It is normally the group or category of the root causes such as hardware issues, or software issues. In practice, each node in the model has been limited to have a maximum of four parent nodes by applying an intermediate layer. This tactic prevents highly complex conditional probability tables, thereby facilitating generation of the diagnostic models. The observation layer can be any information useful for allocating the root cause such as customer's reports, or the outcomes of tests performed by a diagnostic technician. An observation node is affiliated to a specific root node, and each root cause may normally have one or more observations. The intermediate nodes may also have observations. In this case, the observation is useful information indicating the group or category of the likely root causes.

Knowledge collection and analysis

Apart from the existing troubleshooting flow diagrams, the following data sources were accessed for generating the diagnostic model: documentation such as subsystem specific diagnostic specifications, failure mode effect analysis (FMEA); experience of diagnostic engineers; and field information such as warranty databases. Analysis of the documents generated a basic structure for the diagnostic models.

After determining the structure of the model, the prior information required by the model was obtained by the following ways:

– Prior probability required by the root cause layer was generated from the statistical analysis of historic failure data.
– Prior conditional probabilities required by other layers were provided by the domain experts.

The evidence required for Bayesian Network reasoning was provided by customer reports or by diagnostic technicians via a sequence of tests.

Model for symptom "no sound"

A Bayesian diagnostic model for the symptom "no sound" is shown in Fig. 6. The model contains 20 observation nodes drawn with blue ellipses, 13 root cause nodes drawn with amber ellipses, 7 intermediate nodes drawn with green ellipses and 1 symptom node drawn with yellow ellipse. It can been seen that all root cause nodes are set as root layer edge node. This is because prior probability of the root causes can be extracted from statistic analysis of historic fault data while the prior probability of the observation node is often unknown and very difficult to estimate. Table 1 lists the names, signs, categories, discrete states of all nodes, prior probabilities of the root caused nodes and conditional probabilities of the observation nodes. Because the conditional probabilities of the intermediate and symptom nodes are always definite, we

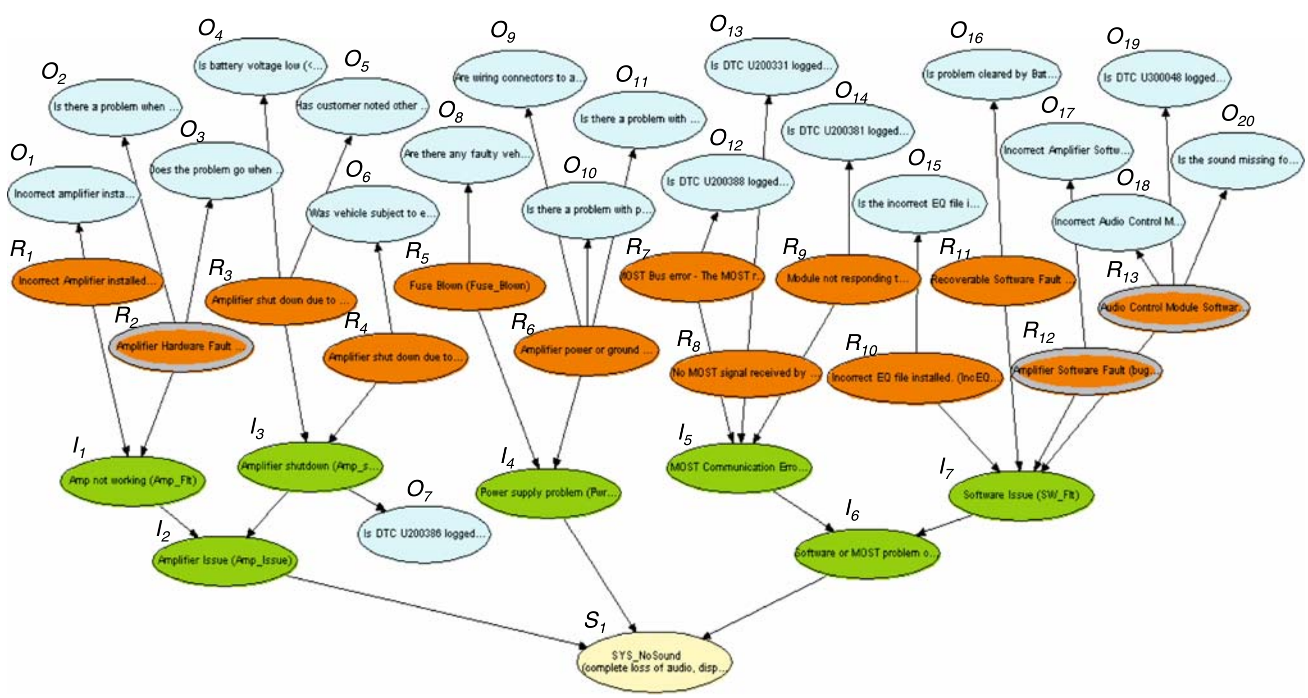


Fig. 6 Bayesian diagnostic model for the symptom "no sound"

Table 1 List of nodes, prior and conditional probabilities

	Node event	Sign	State		Probability
Observation layer	Incorrect amplifier installed?	O_1	T	F	$P(O_1^1/R_1^1) = 1 P(O_1^2/R_1^1) = 0$ $P(O_1^1/R_1^2) = 0 P(O_1^2/R_1^2) = 1$
	Is there a problem when trying to read out software versions	O_2	T	F	$P(O_2^1/R_2^1) = 1 P(O_2^2/R_2^1) = 0$ $P(O_2^1/R_2^2) = 0 P(O_2^2/R_2^2) = 1$
	Does the problem go when a known good Amplifier is fitted	O_3	T	F	$P(O_3^1/R_2^1) = 1 P(O_3^2/R_2^1) = 0$ $P(O_3^1/R_2^2) = 0$ $P(O_3^2/R_2^2) = 1$
	Is battery voltage low (<10.5 V)?	O_4	T	F	$P(O_4^1/R_3^1) = 0.95 P(O_4^2/R_3^1) = 0.05$ $P(O_4^1/R_3^2) = 0 P(O_4^2/R_3^2) = 1$
	Has customer noted other systems warning lights or cutting out which may indicate low battery voltage?	O_5	T	F	$P(O_5^1/R_3^1) = 0.7 P(O_5^2/R_3^1) = 0.3$ $P(O_5^1/R_3^2) = 0.05 P(O_5^2/R_3^2) = 0.95$
	Was vehicle subject to excessively high temperatures when shut down occurred (> 85°C)?	O_6	T	F	$P(O_6^1/R_4^1) = 0.7 P(O_6^2/R_4^1) = 0.3$ $P(O_6^1/R_4^2) = 0 P(O_6^2/R_4^2) = 1$
	Is DTC U200386 logged?	O_7	T	F	$P(O_7^1/I_3^1) = 1 P(O_7^2/I_3^1) = 0$ $P(O_7^1/I_3^2) = 0 P(O_7^2/I_3^2) = 1$
	Are there any faulty vehicle fuses?	O_8	T	F	$P(O_8^1/R_5^1) = 1 P(O_8^2/R_5^1) = 0$ $P(O_8^1/R_5^2) = 0 P(O_8^2/R_5^2) = 1$
	Are wiring connectors to amplifier loose or not properly installed?	O_9	T	F	$P(O_9^1/R_6^1) = 0.9 P(O_9^2/R_6^1) = 0.1$ $P(O_9^1/R_6^2) = 0 P(O_9^2/R_6^2) = 1$
	Is there a problem with power feeds and/or grounds present at amplifier connector?	O_{10}	T	F	$P(O_{10}^1/R_6^1) = 0.8 P(O_{10}^2/R_6^1) = 0.2$ $P(O_{10}^1/R_6^2) = 0 P(O_{10}^2/R_6^2) = 1$
	Is there a problem with Infotainment system earth?	O_{11}	T	F	$P(O_{11}^1/R_6^1) = 0.8 P(O_{11}^2/R_6^1) = 0.2$ $P(O_{11}^1/R_6^2) = 0 P(O_{11}^2/R_6^2) = 1$
	Is DTC U200388 logged?	O_{12}	T	F	$P(O_{12}^1/R_7^1) = 1 P(O_{12}^2/R_7^1) = 0$ $P(O_{12}^1/R_7^2) = 0 P(O_{12}^2/R_7^2) = 1$
	Is DTC U200331 logged?	O_{13}	T	F	$P(O_{13}^1/R_8^1) = 1 P(O_{13}^2/R_8^1) = 0$ $P(O_{13}^1/R_8^2) = 0 P(O_{13}^2/R_8^2) = 1$
	Is DTC U200381 logged?	O_{14}	T	F	$P(O_{14}^1/R_9^1) = 1 P(O_{14}^2/R_9^1) = 0$ $P(O_{14}^1/R_9^2) = 0 P(O_{14}^2/R_9^2) = 1$
	Is the incorrect EQ file installed?	O_{15}	T	F	$P(O_{15}^1/R_{10}^1) = 1 P(O_{15}^2/R_{10}^1) = 0$ $P(O_{15}^1/R_{10}^2) = 0 P(O_{15}^2/R_{10}^2) = 1$
	Is problem cleared by Battery Reset?	O_{16}	T	F	$P(O_{16}^1/R_{11}^1) = 1 P(O_{16}^2/R_{11}^1) = 0$ $P(O_{16}^1/R_{11}^2) = 0 P(O_{16}^2/R_{11}^2) = 1$
	Incorrect Amplifier Software Loaded? (not latest level)	O_{17}	T	F	$P(O_{17}^1/R_{12}^1) = 0.8 P(O_{17}^2/R_{12}^1) = 0.2$ $P(O_{17}^1/R_{12}^2) = 0 P(O_{17}^2/R_{12}^2) = 1$
	Incorrect Audio Control Module Software Loaded? (not latest level)	O_{18}	T	F	$P(O_{18}^1/R_{13}^1) = 0.8 P(O_{18}^2/R_{13}^1) = 0.2$ $P(O_{18}^1/R_{13}^2) = 0.2 P(O_{18}^2/R_{13}^2) = 0.8$
	Is DTC U300048 logged?	O_{19}	T	F	$P(O_{19}^1/R_{13}^1) = 0.9 P(O_{19}^2/R_{13}^1) = 0.1$ $P(O_{19}^1/R_{13}^2) = 0 P(O_{19}^2/R_{13}^2) = 1$
	Is the sound missing for the CD or Radio?	O_{20}	T	F	$P(O_{20}^1/R_{13}^1) = 1 P(O_{20}^2/R_{13}^1) = 0$ $P(O_{20}^1/R_{13}^2) = 0 P(O_{20}^2/R_{13}^2) = 1$
Root cause layer	Incorrect Amplifier installed	R_1	T	F	$P(R_1^1) = 0.054 P(R_1^2) = 0.946$
	Amplifier Hardware Fault	R_2	T	F	$P(R_2^1) = 0.109 P(R_2^2) = 0.891$
	Amplifier shut down due to low voltage	R_3	T	F	$P(R_3^1) = 0.027 P(R_3^2) = 0.973$
	Amplifier shut down due to high temperature	R_4	T	F	$P(R_4^1) = 0.027 P(R_4^2) = 0.973$
	Fuse Blown	R_5	T	F	$P(R_5^1) = 0.109 P(R_5^2) = 0.891$
	Amplifier power or ground not properly connected	R_6	T	F	$P(R_6^1) = 0.109 P(R_6^2) = 0.891$
	MOST Bus error—The MOST ring is cut off (not immediately before IHU)	R_7	T	F	$P(R_7^1) = 0.109 P(R_7^2) = 0.891$
	No MOST signal received by Audio Control Module	R_8	T	F	$P(R_8^1) = 0.054 P(R_8^2) = 0.946$

Table 1 continued

	Node event	Sign	State		Probability
	Module not responding to MOST commands	R_9	T	F	$P(R_9^1) = 0.054 P(R_9^2) = 0.946$
	Incorrect EQ file installed	R_{10}	T	F	$P(R_{10}^1) = 0.109 P(R_{10}^2) = 0.891$
	Recoverable Software Fault	R_{11}	T	F	$P(R_{11}^1) = 0.011 P(R_{11}^2) = 0.989$
	Amplifier Software Fault (bug/error or corruption)	R_{12}	T	F	$P(R_{12}^1) = 0.011 P(R_{12}^2) = 0.989$
	Audio Control Module Software Fault (bug/error or corruption)	R_{13}	T	F	$P(R_{13}^1) = 0.027 P(R_{13}^2) = 0.973$
Intermediate layer	Amp not working	I_1	T	F	
	Amplifier Issue	I_2	T	F	
	Amplifier shutdown	I_3	T	F	
	Power supply problem	I_4	T	F	
	MOST Communication Error	I_5	T	F	
	Software or MOST Problem	I_6	T	F	
	Software Issue	I_7	T	F	
Symptom layer	SYS-NoSound (complete loss of audio, display functions working)	S_1	T	F	

do not list these probabilities in the table. In this study, we use HUGIN software for Bayesian Network propagation and reasoning.

Determination of prior probabilities of root causes

This section explains how to extract the prior probabilities of the root causes from historic fault data. Referring to Fig. 6, the posterior conditional probability $P(R_1/S_1)$ can be obtained from:

$$P(R_1/S_1) = \frac{P(S_1/R_1) \cdot P(R_1)}{P(S_1)} \tag{7}$$

Therefore, prior probability $P(R_1)$ of the root cause R_1 is got by

$$P(R_1) = \frac{P(R_1/S_1) \cdot P(S_1)}{P(S_1/R_1)} \tag{8}$$

We assume if R_1 occurs S_1 must occur, that is the conditional probability $P(S_1/R_1) = 1$. This is true in our applications since all root causes are defined in such a way. Thus,

$$P(R_1) = P(R_1/S_1) \cdot P(S_1) \tag{9}$$

Considering $P(S_1)$ as a scaling factor, Eq. 9 indicates that the prior probabilities of a root cause R_1 can be set as its conditional probability $P(R_1/S_1)$ given the symptom S_1 occurs. In practice, the statistical fault data is available for each failure symptom, that is, the conditional probability of individual root causes given the symptom occurs is known. For example, historic data tells that 10 of 100 "SYS NoSound" failures were caused by root cause R_1 "Incorrect Amplifier installed", that means the conditional probability $P(R_1/S_1) = 0.1$. Accordingly, we can also know conditional probabilities for other root causes including $P(R_1/S_1)$, $P(R_3/S_1)\ldots P(R_{13}/S_1)$. Considering $P(S_1)$ as a scaling factor, these conditional probabilities can be set as prior probabilities of the root causes $R_1 R_2 \ldots R_{13}$. The prior probabilities of the root causes indicate the likelihood that the defect occurs without any evidence. It is worthy noting that the layer of intermediate nodes do not affect the prior probabilities of root causes since the causal relationship between them is definite.

Diagnostic procedure

Diagnosis based on the Bayesian Network Model is an iteration process of ranking the observation node, conducting the test in terms of ranking order, updating probabilities of the all nodes by inputting the test results into the model, determining the most likely defects, repairing the defect and checking if the symptom still exists. This iteration continues until the symptom does not occur any more. In each iteration, the first task is to derive a sequence of tests to effectively locate the real root causes of failures, i.e. ranking the observation nodes in a sensible order. The ranking rules are as follows;

- An intermediate node has higher priority than a root cause node, i.e. observation nodes affiliated to intermediate nodes are always ranked in front of observation nodes affiliated to root cause nodes. This is because the intermediate nodes determine the route from symptom to root causes.
- For observation nodes affiliated to different intermediate nodes or different root cause nodes, the probabilities of the intermediate nodes or root cause nodes determines the priority of the observation nodes affiliated to them.

– For observation nodes affiliated to the same intermediate node or the same root cause node, their own probabilities determine the priority.

In summary, the ranking order is illustrated as Fig. 7.

Referring again to the model in Fig. 6, after establishing the model, we first calculate the probability of the symptom

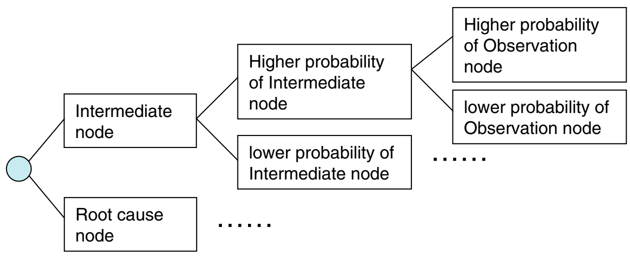


Fig. 7 Priority hierarchy of ranking test sequence

node $P(S_1 = \text{true}) = 57.1\%$ which indicates the likelihood of symptom occurring under no evidence given. Diagnosis starts from instantiating the symptom, i.e. setting $P(S_1 = \text{true}) = 1$. With this initial evidence, the probabilities of one intermediate node, root cause nodes and their affiliated observation nodes are recalculated as listed in Table 2. In terms of the rules of ranking observation nodes, the observation node O_7 is ranked on the top since it is affiliated to the intermediate node I_3. The next suggested tests are O_2, O_3, O_8, O_{12} and O_{15} because their root cause nodes have the highest probability (19.07) amongst all root cause nodes and they also have the highest probability (19.69) amongst all observation nodes belonging to those root cause nodes. Accordingly, the order of the rest of the tests is also indicated in the table.

For guiding the diagnosis, in each diagnosis step, we present all possible root causes marked with their probabilities,

Table 2 The probability list of all nodes and ranking order under initial evidence $P(S_1 = \text{true}) = 1$

Root cause or intermediate nodes	Prob. of true	Affiliated observation nodes	Sign	Prob.	Order
Amplifier shutdown	9.32	Is DTC U200386 logged?	O_7	18.29	1
Amplifier Hardware Fault	19.07	Is there a problem when trying to read out software versions	O_2	19.69	2
		Does the problem go when a known good Amplifier is fitted	O_3	19.69	2
Fuse Blown	19.07	Are there any faulty vehicle fuses?	O_8	19.69	2
MOST Bus error—The MOST ring is cut off (not immediately before IHU).	19.07	Is DTC U200388 logged?	O_{12}	19.69	2
Incorrect EQ file installed.	19.07	Is the incorrect EQ file installed?	O_{15}	19.69	2
Amplifier power or ground not properly connected	19.07	Are wiring connectors to amplifier loose or not properly installed?	O_9	17.97	3
		Is there a problem with power feeds and/or grounds present at amplifier connector?	O_{10}	16.06	4
		Is there a problem with Infotainment system earth?	O_{11}	16.06	4
Incorrect Amplifier installed	9.45	Incorrect amplifier installed?	O_1	10.26	5
No MOST signal received by Audio Control Module	9.45	Is DTC U200331 logged?	O_{13}	10.26	5
Module not responding to MOST commands	9.45	Is DTC U200381 logged?	O_{14}	10.26	5
Audio Control Module Software Fault (bug/error or corruption)	4.72	Incorrect Audio Control Module Software Loaded? (not latest level).	O_{18}	22.83	6
		Is DTC U300048 logged?	O_{19}	5.2	10
		Is the sound missing for the CD or Radio?	O_{20}	5.63	8
Amplifier shut down due to low voltage	4.72	Is battery voltage low (<10.5 V)?	O_4	5.44	9
		Has customer noted other systems warning lights or cutting out which may indicate low battery voltage?	O_5	8.07	7
Amplifier shut down due to high temperature	4.72	Was vehicle subject to excessively high temperatures when shut down occurred (> 85°)?	O_6	4.26	11
Recoverable Software Fault	1.92	Is problem cleared by Battery Reset?	O_{16}	2.89	12
Amplifier Software Fault (bug/error or corruption)	1.92	Incorrect Amplifier Software Loaded? (not latest level).	O_{17}	2.52	13

also list all optional testing ranked according to the order defined by the rules above. The user has a flexibility to conduct one or more tests according to the suggested testing list, or according to their own diagnostic experiences and the level of the difficulty of each individual test. After the user conducts the tests the new evidence (test results) are be input into the model. The model will then recalculate the probabilities of all nodes and generate a new suggested test list and updated probabilities for potential root causes. This process continues until the probability of one root cause has a higher probability convincing the user to repair the defect. If the repair action does not fix the failure (symptom), the user should conduct other tests and repair other suggested defects with highest probability until the symptom no longer exist.

Diagnosis for multiple symptom case

An important advantage of the Bayesian network diagnostic approach is its capability of diagnosing multiple symptoms optimally and simultaneously, thereby leading to a more sensible and efficient diagnosis. To achieve this we need to establish a Bayesian diagnostic model with multiple symptoms. There are two ways to establish such a model. Firstly, we can still use the method described in "Framework of the single symptom diagnostic model" by simply giving multiple symptom nodes to the model. However, this method tends to make the model overly large because each symptom may have many independent root cause nodes. BBNs are a NP-hard problem where computation grows exponentially with system complexity, i.e. the size of the network. Thus, it is not a good way to model multiple symptom cases using a single BBN model. Consequently, 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, Breese, & Rommelse, (1995) 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. 1999 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 with multiple symptoms.

Object oriented BBN structure

The object oriented BBN structure can be described as follows; an object oriented BBN diagnostic model consists of a number of sub-models and residing in a main model. The sub-models are constructed for individual symptoms and contain detailed diagnostic knowledge for diagnosing the specific symptom. The main model links the sub-models in terms of their common root causes and gives an overview of the relationship between multiple sub-models.

The benefits of the object oriented BBN are: (1) Enable modelling of a complex system. (2) Enable simultaneous diagnosis of multiple symptoms. (3) Easy maintenance of the large mount of sub-models. (4) Sub-models can be reused as a class. (5) Probability computation is only allocated to the sub-models with the symptoms instantiated.

In this study, the diagnostic boundary was defined as the infotainment system, but can be extended into a complete vehicle system in virtue of the object oriented method.

Object oriented Bayesian diagnostic model with four symptoms

A BBN diagnostic model with four symptoms has been established. Figure 8 shows the main model which contains four sub-models and three common root causes. Each block in the main model represents a sub-model specified to one particular failure symptom. They are respectively "SYS-NoSound", "SYS-Interference", "IHU-CDFailure" and "IHU-Display-Failure". 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 link those sub-models which have common root causes. Actually, the linked interface nodes are the common root cause nodes, while the input nodes are not real nodes but are placeholders in the sub-models. It can be seen from this figure that the sub-models S_1 and S_2 have two common root causes CR_1 "Amplifier Software Fault (bug/error or corruption)" and CR_2 "Amplifier Hardware Fault". The sub-model S_1, S_3 and $S4_3$ share one common root cause CR_3 "Audio Control Module Software Fault (bug/error or corruption)". The sub-model S_1 "SYS-NoSound" is shown in Fig. 6 where three output nodes are drawn with *thick grey* borders.

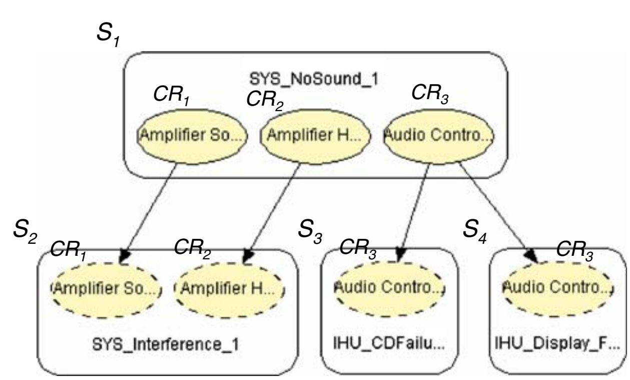


Fig. 8 Main diagnostic model with four sub-models and three common root causes

Determination of prior probabilities of root causes in object oriented model

For each sub-model with a single symptom, we can use the method described in "Framework of the single symptom diagnostic model" to determine the prior probabilities of the root causes because the probability of the symptom can be considered as a scaling factor. However, if two or more sub-models have common root causes and are linked together, we cannot keep the original prior probabilities for the root causes in the model newly generated because the root cause set has been extended. Accordingly, we must consider all root causes of related sub-models as a complete event set. Figure 9 shows the event set for the model shown in Fig. 8. In Fig. 9, S_1, S_2, S_3 and S_4 are the root cause set of four symptoms respectively. S_1 and S_2 have an intersection S_1S_2. S_1, S_3 and S_4 have an intersection $S_1S_3S_4$. R is the root cause only belonging to the set S_2. As defined by the model in Fig. 8, the intersection S_1S_2 consists of the common root causes CR_1 and CR_2, and the intersection $S_1S_3S_4$ only consists of the common root cause CR_3. Therefore, the complete root cause set C of Fig. 9 can be calculated as

$$\begin{aligned} C &= S_1 + S_2 + S_3 + S_4 - S_1S_2 - S_1S_3S_4 \\ &= S_1 + S_2 + S_3 + S_4 - CR_1 - CR_2 - CR_3 \end{aligned} \tag{10}$$

The root cause R is the subset of S_2, thus,

$$P(R) = P(RS_2) = P(R/S_2) \cdot P(S_2) \tag{11}$$

The set S_2 is the subset of C, thus,

$$P(S_2) = P(S_2C) = P(S_2/C) \cdot P(C) \tag{12}$$

Substituting Eq. 12 into Eq. 11 generates

$$P(R) = P(R/S_2) \cdot P(S_2/C) \cdot P(C) \tag{13}$$

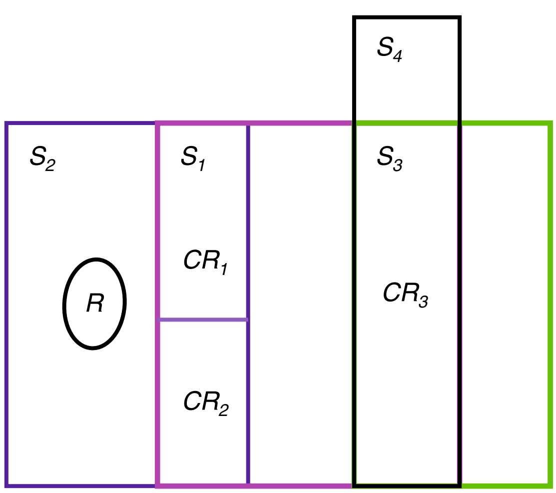


Fig. 9 Root cause event set for four symptoms with three common root causes

Considering $P(C)$ as a scaling factor, we have

$$P(R) = P(R/S_2) \cdot P(S_2/C) \tag{14}$$

The Eq. 14 indicates how to determine prior probability of root causes in the model with multiple linked sub-models. In practice, we can calculate the complete root cause set C using Eq. 10, the conditional probabilities of each sub-model root cause set such as $P(S_2/C)$, and the conditional probabilities of each root cause such as $P(R/S_2)$ from the statistical analysis of historic failure data, and then the prior probability of the root cause can be calculated from Eq. 14. By using this method, the prior probabilities of the root causes in individual sub-models become comparable.

Diagnostic procedure

The diagnostic procedure for multiple symptom cases is basically the same as the single symptom case. The diagnosis starts from the main model. If only one symptom is instantiated, the probability calculation will be limited to the corresponding sub-model. In this case, the suggested tests will be those observation nodes within the sub-model. If two or more symptoms occur simultaneously, the probability propagation will spread to multiple corresponding sub-models. In this case, possible root causes can be the single common root cause, or two or more root causes belonging to different sub-models.

Conclusion

A novel method has been developed for guiding offline vehicle fault diagnosis. The method incorporates the BBN technique. Theoretical analysis on the characteristics of BBN has been given. The proposed method has been practically applied to a model vehicle infotainment system. A number of Bayesian diagnostic models have been established for fault cases with single and multiple symptoms. Special arrangements have been designed for model structure, determination of prior probabilities of root causes, and diagnostic procedure. In order to unburden the computation, an object oriented model structure has been adapted to prevent the model from overly large. It has been demonstrated that, in contrast to the traditional troubleshooting flow diagrams, the proposed method possesses two distinctive advantages. (i) The method is capable of guiding vehicle fault diagnosis in a probabilistic manner, thereby emulating the human way of thinking; (ii) The method features a multiple-symptoms-orientated troubleshooting strategy, and is capable of simultaneously diagnosing multi-symptoms fault cases in an optimised way. These two advantages make automotive fault diagnostics more effective and accurate.

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