A Hierarchical Modeling and Fault Diagnosis Method for Complex Electronic Devices

Bing Long, Shu-Lin Tian, and Hou-Jun Wang

Abstract—Due to the shortcomings of the diagnosis systems for complex electronic devices such as failure models hard to build and low fault isolation resolution, a new hierarchical modeling and diagnosis method is proposed based on multisignal model and support vector machine (SVM). Multisignal model is used to describe the failure propagation relationship in electronic device system, and the most probable failure printed circuit boards (PCBs) can be found by Bayes inference. The exact failure modes in the PCBs can be identified by SVM. The results show the proposed modeling and diagnosis method is effective and suitable for diagnosis for complex electronic devices.

Index Terms—Bayes inference, complex electronic devices, fault diagnosis, hierarchical modeling, support vector machine.

1. Introduction

With rapid improvement of electronic technology, electronic devices become more important in large system such as radars, missiles, aircrafts, satellites, which brings more maintenance problems for these complex electronic devices[1]-[3]. The fault diagnosis technology for electronic devices is widely researched by academic and industry world. Fault dictionary, expert system, fault tree, and neural network are among some successful methods in practical fault diagnosis for electronic devices[1]-[5]. But for fault dictionary and expert system, it is very hard to build fault dictionary and knowledge base, and it is also difficult to validate and maintain the knowledge base. As for neural network, it needs lots of fault samples that are often difficult to obtain for some expensive electronic devices and the diagnostic results are not easy to understand. Multisignal model, which combines the advantage of

dependency model and structural model, was proposed by Deb and Pattipati[6]. The multisignal modeling method, which considers only the fault dependency relationship and not involves the concrete physical specification of the system, can establish uniform model for mechanical and electronic system. What's more, it is easy to create and validate multisignal model and it is very fast to diagnose problems based on this model. Thus, the diagnosis technology based on multisignal model was widely used in space shuttle, international space station, satellite, aircrafts, and so on[7].

But for diagnosis for probable failure in printed circuit boards (PCBs), multisignal model is not the best diagnosis method because it is very difficult to establish the multisignal model for PCBs. Sunil R. Das[8] used built-in hardware for analog and mixed-signal circuits which is not suitable for electronic devices in service. Hu[9] proposed an approach of soft fault diagnosis for analog circuits based on slope fault feature and back propagation neural network. Support vector machine (SVM) is a promising diagnosis method for PCBs because SVM has more advantages than neural network in solving few samples, nonlinearity and high dimensional pattern recognition problems[10]-[12]. SVM are the classifiers that were originally designed for binary classification[13]. Practical PCBs diagnosis problems are multi-class problems. Forming a multi-class classifier by combining several binary classifiers is the way commonly to be used such as one-against-one (o-a-o), one-against-rest (o-a-r) and decision directed acyclic graph (DDAG)[13]. SVM based on binary tree is also a good way for solving multi-class classification problems. We have proposed a new SVM binary decision tree method based on genetic algorithm (GA) that reduces the effect of "accumulative error"[11].

Combining the advantage of multisignal model and SVM, a new modeling and diagnosis method is proposed for complex electronic devices. First, the multisignal model is used to describe the fault dependency relationship for the electronic devices system and the most likely failure PCBs could be found by max Bayes posteriori probability. Second, the exact failure modes in the PCBs can be identified by SVM.

The paper is organized as follows. In Section 2, we give diagnosis algorithm based on multisignal model. Section 3 is devoted to identify the failure modes in PCBs using diagnosis algorithm based on GA-SVM. The proposed

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diagnosis method is validated in a radar receiver system in Section 4. Finally, Section 5 concludes with a summary.

2. Formal Description of Multisignal Modeling and Diagnosis Algorithm

2.1 Formal Description of Multisignal Model

Formally, a multi-signal model can be stated as follows[5],[6]: $S = \{s_1, s_2, \cdots, s_m\}$: a finite set m of independent signals associated with the system, i.e. failure sources; $P = \{P(s_1), P(s_2), \cdots, P(s_m)\}$: a priori probabilities associated with the failure sources; $T = \{t_1, t_2, \cdots, t_n\}$: a finite set of n available tests, suppose T_p is test set not ringing alarm, T_f is test set ringing alarm, that is, $T_p = \{t_i | t_i \text{ not alarm}, t_i \in T\}$, $T_f = \{t_j | t_j \text{ ringing alarm}, t_j \in T\}$, $T = T_p \cup T_f$; $\mathbf{D} = [d_{i,j}]$ is the dependency matrix of failure sources and tests, where $d_{i,j} = 1$ implies that test t_j rings alarm if s_i failure, conversely, $d_{i,j} = 0$ indicates that failures source s_i can not be detected by test t_j .

2.2 Diagnosis Algorithm Based on Multisignal Model

The diagnosis problem is to find the most probable candidate failure source set $S' \subseteq S$ that is consistent with the conditionally independent outcomes of applied tests. This can be formulated as[14],[15]

$$\max_{S' \subseteq S} \text{Prob}(S' | T_p, T_f) . \tag{1}$$

For simplicity, set an indicator vector $\mathbf{K}$, where $k_i = 1$ if failure source $s_i \in X$; $k_i = 0$ otherwise. Using Bayes' theorem:

$$\max_{S' \subseteq S} \text{Prob}(S' | T_p, T_f) = \max_{S' \subseteq S} \text{Prob}(T_p, T_f | S') \frac{\text{Prob}(S')}{\text{Prob}(T_p, T_f)}$$

$$\times \arg\max_{S' \subseteq S} \text{Prob}(T_p, T_f | S')\text{Prob}(S')$$

$$= \arg\max_{S' \subseteq S} \text{Prob}(T_p | S')\text{Prob}(T_f | S')\text{Prob}(S') \tag{2}$$

where

$$\text{Prob}(S') = \prod_{i=1}^{L} p(s_i)^{k_i} (1 - p(s_i))^{(1-k_i)} \tag{3}$$

$$\text{Prob}(T_P | S') = \prod_{t_j \in T_P} \text{Prob}(t_j \in T_p | S') \tag{4}$$

$$\text{Prob}(T_f | S') = \prod_{t_k \in T_f} \text{Prob}(t_k \in T_f | S') \tag{5}$$

$$\text{Prob}(t_j \in T_P | S') = \prod_{i=1}^{L} (1 - d_{i,j})^{k_i} \tag{6}$$

$$\text{Prob}(t_k \in T_f | S') = 1 - \text{Prob}(t_k \in T_P | S') . \tag{7}$$

For each failed test $t_j \in T_f$ (i.e., ringing alarm), the optimal solution contains at least one failure source s_i that satisfies $d_{ij} = 1$. Thus, there must be at least one failure source that accounts for the failure of a test. Suppose $\mathbf{A}$ is the resulting matrix formed from the F-lists, where each row of $\mathbf{A}$ represents the list of failure sources covered by a failed test (called candidate faults). With known good components excluded, the elements of $\mathbf{A}$ corresponding to candidate faults are set to 1, while others are set to 0. The resulting matrix $\mathbf{A}$ should have dimension $T_f \times m$, where T_f represents the number of failed tests.

Equations (2) and (3) can be turned into the following set covering problem (SCP) [14]:

$$\min_{S' \subseteq S^-} \sum_{s_i \in S^-} q_i k_i \tag{8}$$

$$\text{s. t.} \quad \mathbf{AK} \geq \mathbf{e} , \quad k_i \in \{0,1\}, \quad i = 1, 2, \cdots, m \tag{9}$$

where S^- denotes the reduced set after excluding known good components, and

$$q_i = -\ln(p(s_i)/(1 - p(s_i))) , \quad i = 1, 2, \cdots, m . \tag{10}$$

It is well known SCP is NP-hard. We use a heuristic algorithm based on Lagrangian relaxation and subgradient optimization to solve this problem[14], [15].

3. Diagnosis Algorithm Based on GA-SVM

3.1 Binary-Class SVM

Consider a set of n data vectors

$$\{\mathbf{x}_i, y_i\} , \quad i = 1, 2, \cdots, n , \quad y_i = \{-1, 1\}, \quad \mathbf{x}_i \in \mathbf{R}$$

Where $\mathbf{x}_i$ is the ith data vector that belongs to a binary class y_i. We seek the hyper plane which best separates the two classes where by best we mean with the largest margin.

For Linearly separable case, that amounts to finding ω and b so that [10]-[13]:

$$\min_{1 \leq i \leq n} y_i (\omega \cdot \mathbf{x}_i + b) \geq 1 , \quad i = 1, 2, \cdots, n \tag{11}$$

i.e., so that the distance between the closest point to the hyperplane is $1/\|\omega\|$, $\|\omega\|$ is the L2-norm of ω . Among the separating hyperplanes, the one for which the distance to the closest point is maximal is called optimal separating hyperplane (OSH). The quantity $2/\|\omega\|$ is called the margin, and thus the OSH is the separating hyperplane which maximizes the margin. The meaning of OSH and the margin can be found in Fig. 1.

Finding the OSH is to finding ω and b to satisfy

$$\min \frac{1}{2}\|\omega\|^2 \tag{12}$$

$$\text{Subject to} \quad y_i (\omega \cdot \mathbf{x}_i + b) \geq 1 \tag{13}$$
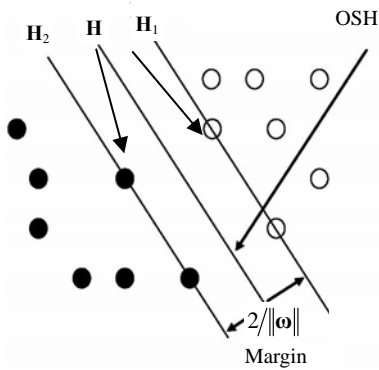
Fig. 1. Sketch of optimal separating hyperplane.

This can be solved by Lagrange multipliers. If we denote by $\boldsymbol{\alpha} = (\alpha_1, \alpha_2, \cdots, \alpha_n)$ the n non negative Lagrange multipliers associated with constraints (13), our optimization problem amounts to maximizing

$$Q(\boldsymbol{\alpha}) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j \mathbf{x}_i \cdot \mathbf{x}_j \qquad (14)$$

with $\alpha_i > 0$ and under constraint $\sum_{i=1}^{n} y_i \alpha_i = 0$. This can be achieved by the use of standard quadratic programming methods.

Once the vector $\boldsymbol{\alpha}^0 = (\alpha_1^0, \alpha_2^0, \cdots, \alpha_n^0)$ solution of the maximization problem (14) has been found, the OSH($\boldsymbol{\omega}_0, b_0$) has the following expansion:

$$\boldsymbol{\omega}^0 = \sum_{i=1}^{n} \alpha_i^0 y_i \mathbf{x}_i \qquad (15)$$

The support sectors (SV) are the points for which $\alpha_i^0 > 0$ satisfy (13) with equality and also can be found in Fig. 1. The hyperplane decision function can thus be written as

$$f(\mathbf{x}) = \mathrm{sgn}\left(\sum_{i=1}^{n} \alpha_i^0 y_i \mathbf{x}_i \cdot \mathbf{x}_j + b_0 \right) \qquad (16)$$

For linearly nonseparable and nonlinear case, we can obtain similar results. You can find the detail in reference [10]-[13].

3.2 Multi-Class SVM GA-Based Decision-Tree

It is proved that decision tree is an effective method which can turn multi-class problem into binary-class problem[10]-[13]. But there is important effect for classified resolution for different decision tree structure which may produce the effect of "accumulative error". So how to construct the optimal (or near optimal) binary decision tree is the key point of multi-class SVM based on decision tree. According to max class margin, genetic algorithm (GA) is used to construct optimal (or near optimal) decision tree[11]. SVM decision tree generation algorithm based on GA-SVM algorithm is shown as Fig. 2. Due to GA is adopted in each new node generation, different classification problems can generate different decision trees. So GA-SVM has auto adaptability to reduce the effect of "accumulative error". But it needs to note that GA is a
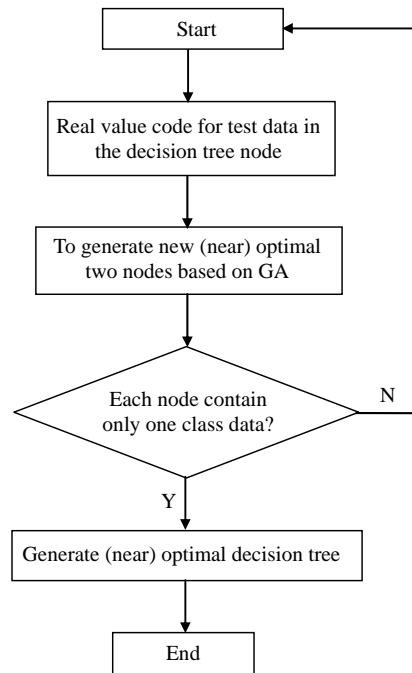

Fig. 2. SVM decision tree generation algorithm based on GA-SVM algorithm.

heurist search algorithm which means that the generation decision tree is not always optimal, may be near optimal decision tree.

4. Application to a Radar Receiver System

According to multisignal modeling method[5],[6], the multisignal model for a radar receiver system is established and the dependency matrix is shown in Table 1.

Then based on max Bayes posteriori probability principle, a heuristic algorithm, using Lagrangian relaxation and subgradient optimization[14], is used to find approximately the most likely candidate fault set (i.e. PCBs). Then the exact failure modes in the PCBs can be identify by GA-SVM[11].

For failure modes identification based on SVM, it needs to collect the failure data and generate the SVM multiple classless decision trees using GA-SVM algorithm mentioned above according to different failure modes of different failure source of the radar receiver. Then the trained SVM decision tree is stored in database of the diagnosis system. The real-time collected data in field is fed into the diagnosis system and the failure modes can be identified by these decision trees. Now a linear amplifier in the radar receiver is used to illustrate the GA-SVM generation. The scheme of the amplifier is shown as Fig. 3.

The common failure modes for the amplifier are transistor burn, resistor open, capacitor burst, etc. Here seven typical failure modes (transistor Q_1 burn; resistor R_{11} open; transistor Q_4 burn; capacitor C_{21} burst; capacitor C_{37} burst; resistor R_{25} open; transistor Q_9 burn) are selected.
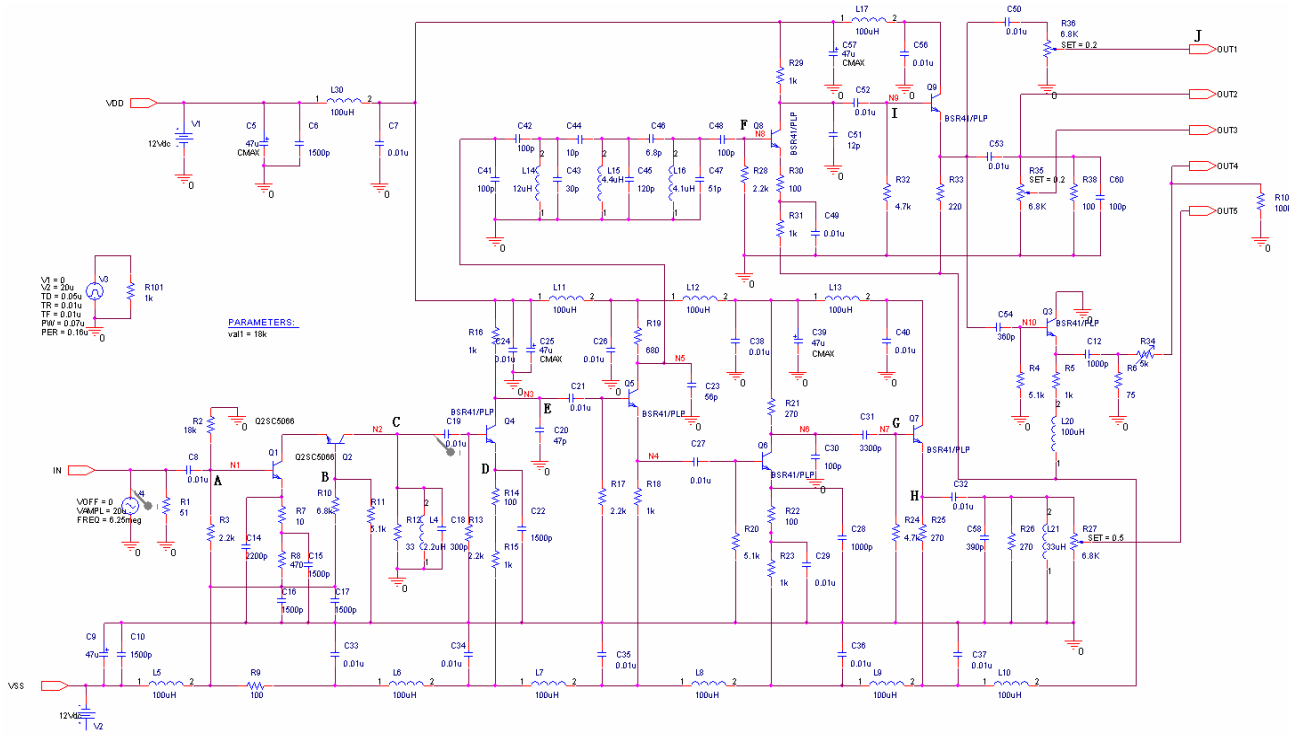
Fig. 3. Scheme of the amplifier in the receiver.

Table 1: Dependency matrix for the receiver

C/T	t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8	t_9	t_{10}	t_{11}	t_{12}	t_{13}	t_{14}
$c_1(G)$	1	1	1	1	1	1	1	1	1	1	1	1	1	0
$c_2(G)$	0	1	0	1	0	1	1	0	1	1	1	1	1	0
$c_2(F)$	0	1	0	1	0	1	1	0	1	1	1	0	0	0
$c_3(G)$	0	0	1	1	0	1	0	0	1	1	1	1	0	0
$c_4(G)$	0	0	0	1	0	1	1	0	1	1	1	1	1	0
$c_4(F)$	0	0	0	1	0	1	1	0	1	0	1	0	0	0
$c_5(G)$	0	0	0	0	1	0	0	1	1	1	1	1	1	0
$c_6(G)$	0	0	0	0	0	1	1	0	1	1	1	1	1	0
$c_6(F)$	0	0	0	0	0	1	1	0	1	0	1	0	0	0
$c_7(G)$	0	0	0	0	0	0	1	1	1	1	1	1	1	0
$c_7(F)$	0	0	0	0	0	0	1	0	0	0	0	1	1	0
$c_8(G)$	0	0	0	0	0	0	0	1	1	1	1	1	1	0
$c_9(G)$	0	0	0	0	0	0	0	0	1	1	1	1	1	0
$c_9(F)$	0	0	0	0	0	0	0	0	1	0	1	0	0	0
$c_{10}(G)$	0	0	0	0	0	0	0	0	0	1	0	1	1	0
$c_{11}(G)$	0	0	0	0	0	0	0	0	0	0	1	0	0	0
$c_{12}(G)$	0	0	0	0	0	0	0	0	0	0	0	1	0	0
$c_{13}(G)$	0	0	0	0	0	0	0	0	0	0	0	0	1	1
$c_{14}(G)$	0	0	0	0	1	1	1	1	1	1	1	1	1	1
$c_{14}(F)$	0	0	0	0	1	0	0	1	0	0	0	1	1	1

According to the scheme of the circuits, 10 test points A-J are set to collect the voltage value. There exist different data at point A-J for different failure modes. Thus the data vector from these points' data can be used as failure feature vector. The failure data for the amplifier is generated by Monte Carlo simulation using OrCAD/PsPice 9.2. Using the 20 group simulation failure data as SVM training data, the GA-SVM decision tree is generated, as shown in Fig. 4 and stored in database of the diagnosis system.

After the multisignal model for the radar receiver system and the GA-SVM failure modes identification models are established, the integrated diagnosis system for the radar receiver system are developed using VC++6.0 and SQL Sever 2000. The diagnosis software is shown in Fig. 5. The experiment results validate the effectiveness of our proposed method.
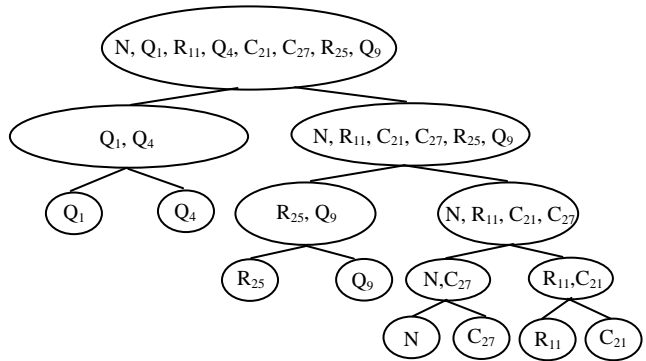

Fig. 4. GA-SVM decision tree for amplifier.

Fig. 5. Final diagnosis results in a test of the radar receiver.

5. Conclusions

Combining the advantages of multisignal model and SVM, a new modeling and diagnosis method is proposed for complex electronic devices. The experiment results show:

1) The proposed diagnosis method can isolate failures to not only PCBs but also failure modes in PCBs which has higher fault isolation resolution than other diagnosis system;

2) GA-SVM has higher precision than the traditional methods to deal with SVM multi-class classification problem.

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