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
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:\cite{5,6}:
\[ S = \{s_1, s_2, \ldots, s_n\} \] : a finite set \( m \) of independent signals associated with the system, i.e. failure sources; \( P = \{P(s_1), P(s_2), \ldots, P(s_n)\} \) : a priori probabilities associated with the failure sources; \( T = \{t_1, t_2, \ldots, t_s\} \) : 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, \( T_p = \{t_i|t_i \text{ not alarm}, t_i \in T\} \), \( T_f = \{t_i|t_i \text{ ringing alarm}, t_i \in T\} \); \( T = T_p \cup T_f \); \( D = \{d_{ij}\} \) is the dependency matrix of failure sources and tests, where \( d_{ij} = 1 \) implies that test \( t_j \) rings alarm if \( s_i \) failure, conversely, \( d_{ij} = 0 \) 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:\cite{14,15}
\[
\max_{S \subseteq S} \text{Prob}(S'|T_p, T_f). \tag{1}
\]
For simplicity, set an indicator vector \( K \), where \( k_i = 1 \) if failure source \( s_i \in X \); \( k_i = 0 \) otherwise. Using Bayes’ theorem:
\[
\max_{S \subseteq S} \text{Prob}(S'|T_p, T_f) = \max_{S \subseteq S} \text{Prob}(T_p, T_f | S') \frac{\text{Prob}(S')}{\text{Prob}(T_p, T_f)}
\]
\[
\times \arg \max_{S \subseteq S} \text{Prob}(T_p, T_f | S')\text{Prob}(S') = \arg \max_{S \subseteq S} \text{Prob}(T_f | S')\text{Prob}(S') \tag{2}
\]
where
\[
\text{Prob}(S') = \prod_{i=1}^{n} p(s_i)^{k_i}(1 - p(s_i))^{1-k_i} \tag{3}
\]
\[
\text{Prob}(T_p | S') = \prod_{t_i \notin T_p} \text{Prob}(t_i \in T_p | S') \tag{4}
\]
\[
\text{Prob}(T_f | S') = \prod_{t_i \in T_f} \text{Prob}(t_i \in T_f | S') \tag{5}
\]
\[
\text{Prob}(t_j \in T_f | S') = \prod_{i=1}^{n} (1 - d_{ij})^{k_i} \tag{6}
\]
\[
\text{Prob}(t_j \in T_f | S') = 1 - \text{Prob}(t_j \in T_p | S') \tag{7}
\]
For each failed test \( t_j \), (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 \( A \) is the resulting matrix formed from the F-lists, where each row of \( A \) represents the list of failure sources covered by a failed test (called candidate faults). With known good components excluded, the elements of \( A \) corresponding to candidate faults are set to 1, while others are set to 0. The resulting matrix \( A \) 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):\cite{14}:
\[
\min_{S \subseteq S} \sum_{s \in S} q_{ks} \tag{8}
\]
subject to \( AK \geq e \), \( k_i \in [0,1], i = 1,2,\ldots,m \) (9)
where \( S' \) denotes the reduced set after excluding known good components, and
\[
q_i = - \ln(p(s_i)/(1 - p(s_i))), i = 1,2,\ldots,m. \tag{10}
\]
It is well known SCP is NP-hard. We use a heuristic algorithm based on Lagrangian relaxation and subgradient optimization to solve this problem\cite{14,15}.

3. Diagnosis Algorithm Based on GA-SVM

3.1 Binary-Class SVM

Consider a set of \( n \) data vectors
\[
\{x_i, y_i\}, i = 1,2,\ldots,n, y_i = \{-1,1\}, x_i \in \mathbb{R}
\]
Where \( x_i \) is the \( i \)th data vector that belongs to a binary class \( y_i \). We seek the hyperplane which best separates the two classes where by best we mean with the largest margin.

For Linearly separable case, that amounts to finding \( \omega \) and \( b \) so that\cite{10,13}:
\[
\min_{1 \leq i \leq n} y_i (\omega \cdot x_i + b) \geq 1, \quad i = 1,2,\ldots,n \tag{11}
\]
i.e., so that the distance between the closest point to the hyperplane is \( 1/\|\omega\| \), \( \|\omega\| \) is the L2-norm of \( \omega \). 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 \( \omega \) and \( b \) to satisfy
\[
\min \frac{1}{2} \|\omega\| \tag{12}
\]
subject to \( y_i (\omega \cdot x_i + b) \geq 1 \) (13)
This can be solved by Lagrange multipliers. If we denote by \( \alpha = (\alpha_1, \alpha_2, \ldots, \alpha_n) \) the \( n \) non-negative Lagrange multipliers associated with constraints (13), our optimization problem amounts to maximizing

\[
Q(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j x_i \cdot x_j
\]

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

Once the vector \( \alpha^0 = (\alpha_1^0, \alpha_2^0, \ldots, \alpha_n^0) \) solution of the maximization problem (14) has been found, the OSH(\( \omega_0, b_0 \)) has the following expansion:

\[
\omega^0 = \sum_{i=1}^{n} \alpha_i^0 y_i x_i
\]

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

\[
f(x) = \text{sgn} \left( \sum_{i=1}^{n} \alpha_i^0 y_i x_i \cdot x_j + b_0 \right)
\]

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 heuristic 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 Q1 burn; resistor R11 open; transistor Q4 burn; capacitor C21 burst; capacitor C37 burst; resistor R25 open; transistor Q6 burn) are selected.
Fig. 3. Scheme of the amplifier in the receiver.

Table 1: Dependency matrix for the receiver

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

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.
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.

Acknowledgment

The authors would like to thank Dr. Lianke for the extensive discussions on the subject and UESTC for its support under Grant No. JX0756, Y2018023601059.

References


Bing Long was born in Sichuan Province, China, in 1974. He received the M.S. degree in structure engineering from Harbin Engineering University, Harbin, in 2002 and the Ph.D. degree in aircraft design from Harbin Institute of Technology, Harbin, in 2005. He is currently an associate professor with School of Automation, University of Electronic Science and Technology of China (UESTC). His research interests include testability analysis and fault diagnosis of electronic systems.

Shu-Lin Tian was born in Hubei Province, China, in 1968. He received his B.S. and M.S. degrees both in measuring and testing technology and instruments from UESTC in 1989 and 1991, respectively. He is now a professor and the Dean of School of Automation Engineering, UESTC. His research interests include high speed, high precision data acquisition and processing, testability analysis and fault diagnosis.

Hou-Jun Wang was born in Beijing, China, in 1961. He received his M.S. and Ph.D. degrees from UESTC in information and signal processing, in 1985 and 1992, respectively. He is now the Vice President of UESTC. His research interests include time domain measurement and signal processing, design for testability of complex system, architecture of auto test system, and fault diagnosis.