Board-Level Functional Fault Diagnosis Using Learning Based on Incremental Support-Vector Machines

Motivation

- Automated and accurate diagnosis
- Reduced diagnosis and repair costs
- Accelerate product release
- Self-learning

- Report ambiguity
- Develop new tests
Board-level Test Techniques

- Auto Optical/X-Ray Inspection
- Boundary-scan test
- In-circuit Test
- Functional Test
- Burn-in test

Case-based Learning

- Bypass bottleneck of rule-based learning
  - Difficult to acquire knowledge needed to build rules
- Bypass bottleneck of model-based learning
  - Difficult to construct model for complex system
- Ease of implementation
- Diagnostic accuracy improves with continuous learning
Learning For Board-level Functional Diagnosis

- Bayesian inference [Zhang VTS’10]
- Artificial neural networks [Zhang ITC’11]
- Support vector machines [Zhang ETS’12]
- Decision trees [Ye ATS’12]

Flowchart for Automated Diagnosis
Diagnosis System Update Mechanism

Input
- Circuit board fault syndromes

SVM Diagnosis Engine
- Enhance
- Adjust

Output
- Suggested repair component

Same as actual root-cause component?
- Yes
- No
  - Report ambiguity
  - Develop new tests

Incremental SVMs

- Key ideas:
  - Dynamic learning, diagnosis system updates
  - Rely on SVMs

- Advantage:
  - Reduce training/computation time
  - Appropriate for online diagnosis in manufacturing line
  - Scalable for diagnosis during high-volume production
Support Vector Machines (SVMs)

Objective function:
Minimize $W = \frac{1}{2} \|w\|^2 + C \sum_{i} \xi_i$

Subject to:
- $\|y_i (w \cdot x_i + b)\| \leq 1 - \xi_i, \forall i$
- $\xi_i > 0$

Incremental SVMs

Object function $W' = \frac{1}{2} \|w'\|^2 + C \sum_{i} (L \cdot \xi_i + \xi_i')$
### Fault Syndromes And Repair Actions

- A segment of the log file of traffic test

```plaintext
# Summary: Interfaces< r2d2 – metro > counts - Fail(mismatch)
...464. (00000247) ERR EG R2D2_ARIC_CP_DBUS_CRC_ERR
... Error: (0000010A) DIAGERR_ERRISO_INVALID_PKT_CNT: Packet count invalid
```

- Syndromes are parsed in multiple dimensions
  - Error ID; mismatched interface; drop counter; component with interrupts; interrupt bits, etc.
  - E.g. Error ID: Mismatched interface: r2d2 – metro, etc.
- Actions are replaced components, e.g. U37

#### Example of iSVMs

**Initial training set**

\[ \mathcal{A} = [B|C] = \begin{bmatrix} 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & -1 \\ 0 & 0 & 1 & -1 \end{bmatrix} \]

**Support vector extraction**

**Extracted support vectors**

\[ \mathcal{A}' = \begin{bmatrix} 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & -1 \\ 0 & 0 & 1 & -1 \end{bmatrix} \]

**Combined Training Set**

\[ \mathcal{D} = \frac{\mathcal{A}'}{\mathcal{N}} = \begin{bmatrix} 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & -1 \\ 0 & 0 & 0 & -1 \\ 0 & 0 & 0 & -1 \\ 0 & 1 & 0 & -1 \end{bmatrix} \]

**New training cases**

\[ \mathcal{N} = \begin{bmatrix} 0 & 0 & 1 & 1 \\ 1 & 1 & 1 & -1 \\ 1 & 0 & 1 & -1 \end{bmatrix} \]
Incremental Learning Flowchart

New training (incoming) data

Failing boards

Preparation stage

Extract fault syndromes and repair actions as additional training set $S$

Learning stage

Existing SVM model

Existing support vectors $S^*$

Optimization problem (10) for combined training set ($S \cup S^*$)

Solve and update SVM model

More new training data?

Yes

No

Final SVM model

Diagnosis stage for new boards

Determine root cause based on the output of final SVM model

Experiments

• Experiments performed on boards currently in production
  – Tens of ASICs, hundreds of passive components
• All the boards under analysis failed traffic test
  – A comprehensive functional test set for fault isolation, run through all components

<table>
<thead>
<tr>
<th></th>
<th>Board 1</th>
<th>Board 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of syndromes</td>
<td>207</td>
<td>420</td>
</tr>
<tr>
<td>Number of root-cause component</td>
<td>14</td>
<td>37</td>
</tr>
<tr>
<td>Number of failed boards</td>
<td>1400</td>
<td>3700</td>
</tr>
</tbody>
</table>
Comparison Of Training Time

Number of training cases in SVMs for Board 1

Comparison Of Training Time

Number of training cases in SVMs for Board 2
Comparison of Success Rates

SVM model success rate (percentage)

Number of training cases in SVMs for Board 1

Comparison of Success Rates

SVM model success rate (percentage)

Number of training cases in SVMs for Board 2
Conclusions

- Manufacturing test and fault diagnosis affect product quality, time-to-market, yield, and cost
- Proposed diagnose system based on incremental SVMs can achieve high diagnosis accuracy
- Reduced diagnose-system update time
  - Scalable to production in high volume

Adaptive Board-Level Functional Fault Diagnosis Using Decision Trees
Current Diagnosis System

- Number of syndromes (up to 1,000 per board)
- Diagnosis time (up to several hours per board)
- Often require manual diagnosis

Decision Trees

- **Internal Nodes**
  - Can branch to two child nodes
  - Represent syndromes

- **Terminal Nodes**
  - Do not branch
  - Contain class information
Decision Trees

- We may reach root cause A1 in two different test sequences.

1) Start from the most discriminative syndrome S1
2) If S1 manifests itself, we then consider syndrome S2
3) If S2 manifests itself, we can determine A1 to be the root cause

Decision Trees

- We may reach root cause A1 in two different test sequences.

1) Start from the most discriminative syndrome S1
2) If S1 pass, we will consider syndrome S3
3) If S3 manifests itself, we will consider syndrome S4
4) If S4 manifests itself, then we can determine A1 to be the root cause
Training Of Decision Trees (Syndrome Identification)

• Goals:
  – Rank syndromes
  – Minimize ambiguity
  – Reduce tree depth

• Three popular criteria can be used for training decision trees
  – Information Gain
  – Gini Index
  – Twoing

**Information Gain**

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C$</td>
<td>A set of training cases (failed boards)</td>
</tr>
<tr>
<td>$A$</td>
<td>A set of root cause component ${A_1, A_2, ..., A_j}$</td>
</tr>
<tr>
<td>$S$</td>
<td>A set of syndromes ${S_1, S_2, ..., S_m}$</td>
</tr>
</tbody>
</table>

\[
IG(C, S_i) = E(C) - E(C|S_i)
\]

- $E(C)$: entropy of $C$
- $E(C|S_i)$: entropy of $C$ given a syndrome $S_i$
- $p(A_j)$: probability of class $A_j$ in $C$
- $s_i$: event that $S_i$ manifest itself; $\overline{s_i}$ otherwise
Information Gain (Example)

First, calculate the entropy of \( C \):

\[
E(C) = E(3:2)
\]

\[
= - \frac{3}{5} \log_2 \frac{3}{5} - \frac{2}{5} \log_2 \frac{2}{5}
\]

\[= 0.673\]

Information Gain (Example)

Consider \( S_1 \):

\[
E(A_1 | S_1) = E(3:0)
\]

\[
= - \frac{3}{3} \log_2 \frac{3}{3} - \frac{0}{3} \log_2 \frac{0}{3} = 0
\]

\[
E(A_2 | S_1) = E(1:1)
\]

\[
= - \frac{1}{2} \log_2 \frac{1}{2} - \frac{1}{2} \log_2 \frac{1}{2}
\]

\[= 0.69\]
Information Gain (Example)

- Consider $S_1$

$$E(A_1|S_1) = 0$$
$$E(A_2|S_1) = 0.69$$

$$E(C|S_1) = 0 \times \frac{3}{5} + 0.693 \times \frac{2}{5} = 0.277$$

$$IG(C,S_1) = E(C) - E(C|S_1) = 0.396$$

Also consider $S_2$, $S_3$

$$IG(C,S_1) = 0.396$$
$$IG(C,S_2) = 0.673$$
$$IG(C,S_3) = 0.298$$

- Since $S_2$ has the highest information gain, we choose $S_2$ to be the most discriminative syndrome
Gini Index

\[ GI(C, S_i) = Gini(C|S_i) - Gini(C) \]

- \( Gini(C) \) is the Gini index of \( C \)
- \( Gini(C|S_i) \) is the Gini index of \( C \) given syndrome \( S_i \)

---

Gini Index (Example)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th>Root Cause</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>( A_1 )</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>( A_1 )</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>( A_1 )</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>1</td>
<td>( A_2 )</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>1</td>
<td>( A_2 )</td>
</tr>
</tbody>
</table>

- Consider Gini index of \( C \)

\[
Gini(C) = E(3:2) = \frac{3}{5} \left( 1 - \frac{3}{5} \right) + \frac{2}{5} \left( 1 - \frac{2}{5} \right) = 0.48
\]
Gini Index (Example)

- Consider Gini Index of $S_1$, $S_2$, and $S_3$
  
  \[ GI(C, S_1) = -0.28 \]
  
  \[ GI(C, S_2) = -0.48 \]
  
  \[ GI(C, S_3) = -0.21 \]

<table>
<thead>
<tr>
<th>$S_1$</th>
<th>$S_2$</th>
<th>$S_3$</th>
<th>Root Cause</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>$A_1$</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>$A_1$</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>$A_1$</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>1</td>
<td>$A_2$</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>1</td>
<td>$A_2$</td>
</tr>
</tbody>
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Diagnosis Using Decision Trees

- **Training Data Preparation**
  Extract all the fault syndromes and the repair actions from historical data

- **DT Architecture Design**
  Design inputs, outputs, splitting criterion, pruning

- **DT Training**
  Generate a tree-based predictive model and assess the performance

- **DT-based Diagnosis**
  Traverse from the root node of DTs and obtain the root cause at the leaf node
Diagnosis Using Decision Trees

Start Diagnosis
Observe the syndrome at the root of DTs

Adaptive Diagnosis
Select and observe the new syndrome based on the observation of current syndrome

Is Leaf Node?
Yes

Predict Root Cause
Generate root cause for the failing board

No

Experiments

- Experiments performed on industrial boards currently in production
  - Tens of ASICs, hundreds of passive components
- All the boards under analysis failed traffic test
  - A comprehensive functional test set for fault isolation, run through all components

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<th></th>
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<th>Board 2</th>
<th>Board 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of test items</td>
<td>420</td>
<td>207</td>
<td>420</td>
</tr>
<tr>
<td>Number of root cause components</td>
<td>10</td>
<td>14</td>
<td>10</td>
</tr>
<tr>
<td>Number of failed boards</td>
<td>130</td>
<td>40</td>
<td>1000</td>
</tr>
</tbody>
</table>
Comparison Of Different Decision-Tree Architectures

Total number of syndromes used for diagnosis

- Board 1
- Board 2
- Board 3

- DT(Gini index)
- DT(Info. Gain)
- DT(Twoing)
- ANNs
- SVMs

Average Number of syndromes used for diagnosis

- Board 1
- Board 2
- Board 3

- DT(Gini index)
- DT(Info. Gain)
- DT(Twoing)
- ANNs
- SVMs
Comparison Between DTs And SVMs

- Success rates (SR) obtained for Board 3

  - SR obtained by DTs are similar to SR obtained by SVMs

Comparison Between DTs And ANNs

- Success rates (SR) obtained for Board 3

  - SR obtained by DTs are similar to SR obtained by ANNs
Conclusions

• Decision tree simplifies board diagnosis
  – Simple structure, less time for training and on-line diagnosis
  – Bypass “test item” bottleneck of existing methods
• Reduced number of syndromes for industry boards
  – A total of 92 test items (syndromes) in DT diagnosis compared to a total of 420 test items in ANNs/SVMs diagnosis
• Different architectures available based on information theory measures
• High success rates
  – Similar success rates obtained using DTs compared to success rates obtained with ANNs/SVMs
• Scalable to diagnosis for production in volume