# An Observation-based Model for Fault Localization

**R. Abreu** P. Zoeteweij A.J.C. van Gemund

Delft University of Technology

WODA, July 2008

TU Delft

# Motivation

## Situation

- SW Debugging is overly expensive
- Many debugging tools/approaches
- Model-based (MBD)
- Dynamic/statistics-based (SFL)

## Rationale

- MBD needs a model as input which is often not available
- SFL cannot distinguish components with the same execution pattern

## In this presentation, a new novel approach...

- Dynamic information to extract a model ▷ inspired by SFL
- Candidates ranked using Bayes' update ▷ inspired by MBD

# Outline

# Components, Runs, Program Spectra...

- A program under analysis comprises a set of **M** components
  - Statements in the context of this paper
- The program is executed using **N** test cases (runs)
- Component activity is recorded in terms of *program spectra*
  - program spectra = abstractions of program traces
- Program spectra is a set of counter or flags for each component
  - In this presentation, *statement-hit spectra* is used

# Observation Matrix

- Row $O_{i\star}$ indicates whether a component was involved in run $i$
- Column $O_{\star j}$ indicates in which runs component $j$ was involved
- The error vector $e$ indicates whether a run has failed or passed

$$N \text{ spectra} \quad O = \left[\begin{array}{cccc|c} o_{11} & o_{12} & \cdots & o_{1M} & e_1 \\ o_{21} & o_{22} & \cdots & o_{2M} & e_2 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ o_{N1} & o_{N2} & \cdots & o_{NM} & e_N \end{array}\right]$$

($M$ components; error vector)

- Input to the debugging method is **only** $O$

# Outline

# Model Generation

- Compile the observation matrix into propositional logic
  - More specifically, conjunctions of disjunctions
- Suppose the following source code and program spectra

```
    (y1,y2) 3inv(bool x) {
1.    w = !x
2.    y1 = !w;
3.    y2 = w; //fault: ! missing
      return (y1,y2);
    }
```

| $c_1$ | $c_2$ | $c_3$ | $e$ | |
|---|---|---|---|---|
| 1 | 1 | 0 | 0 | $obs_1$ |
| 1 | 0 | 1 | 1 | $obs_2$ |
| 0 | 1 | 1 | 1 | $obs_3$ |

- Yields the following propositional logic

$$(\neg h_1 \vee \neg h_3) \wedge (\neg h_2 \vee \neg h_3)$$

# Solve the Model

- Compute the minimal hitting set
  - NP complete
  - TUDelft heuristic: STACCATO
- The solution for the example's model

$$(\neg h_1 \vee \neg h_3) \wedge (\neg h_2 \vee \neg h_3)$$

$$\Downarrow$$

$$(\neg h_3) \vee (\neg h_1 \wedge \neg h_2)$$

- Thus, either $\mathbf{c_3}$ is faulty **or** $\mathbf{c_1}$ and $\mathbf{c_2}$ are faulty

# Ranking Diagnoses

- Set of diagnosis candidates can be large
- Bayes' update to compute probabilities

$$\Pr(d_k|obs) = \frac{\Pr(obs|d_k)}{\Pr(obs)} \cdot \Pr(d_k)$$

where

- $\Pr(d_k) = p^{|d_k|} \cdot (1-p)^{M-|d_k|}$ and, e.g., $p = 0.01$
-

$$\Pr(obs|d_k) = \begin{cases} 0 & \text{if } \mathrm{SD} \wedge obs \wedge d_k \models \bot \\ 1 & \text{if } d_k \rightarrow obs \wedge \mathrm{SD} \\ \varepsilon & \text{if } d_k \rightarrow \{obs_1 \wedge \mathrm{SD}, \ldots, obs \wedge \mathrm{SD}, \ldots, obs_k \wedge \mathrm{SD}\} \end{cases}$$

-

$$\varepsilon = \begin{cases} g(d_k)^t & \text{if run passed} \\ 1 - g(d_k)^t & \text{if run failed} \end{cases}$$

# Ranking Diagnoses, ctd'ed

- $g$ estimates the probability that components in $d_k$ produce a correct output

$$g(d_k) = \frac{\sum_{i=1..N} [(\bigvee_{j \in d_k} o_{ij} = 1) \wedge e_i = 0]}{\sum_{i=1..N} [\bigvee_{j \in d_k} o_{ij} = 1]}$$

- Back to our example...

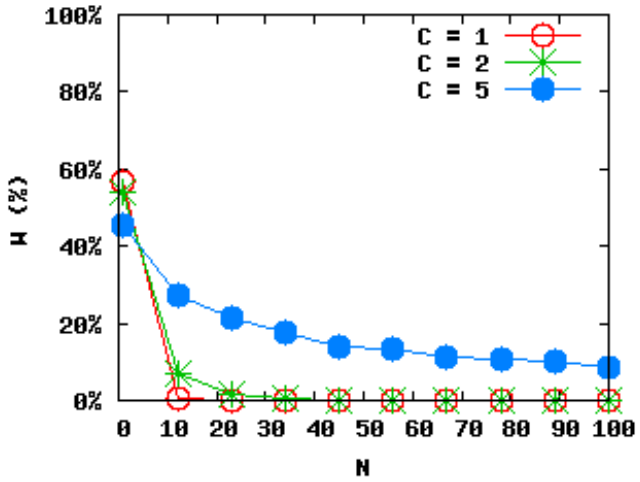
| $d_k$ | $\Pr(d_k)$ |
|---|---|
| {3} | 0.995 |
| {1,2} | 0.005 |

- Meaning that, one would start by inspecting component 3

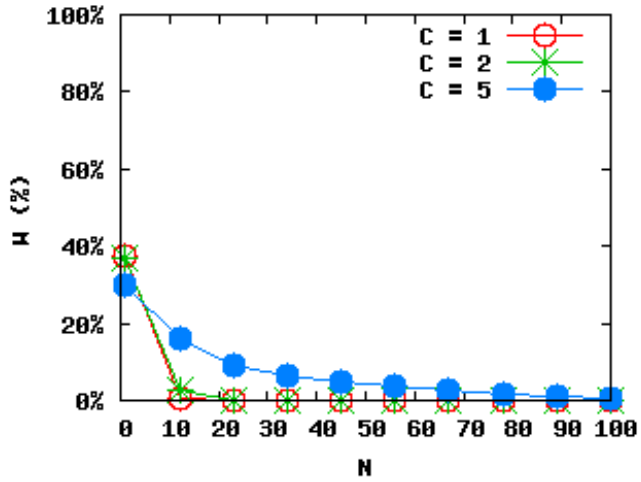
# Outline

# Experimental Setup

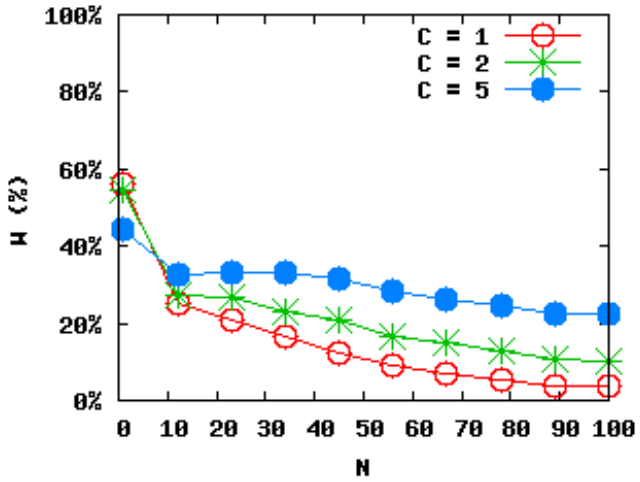
- Study the effects of the following on the diagnostic accuracy
  - Number of Failing Runs
  - Behavior for Small Number of Runs
  - Behavior for Large Number of Runs
- Observation matrices built based on
  - Probability a component is touched $r$
  - Probability a faulty component fails $g$
  - Fault cardinality $C$
- Evaluation Metric: *Wasted Effort*



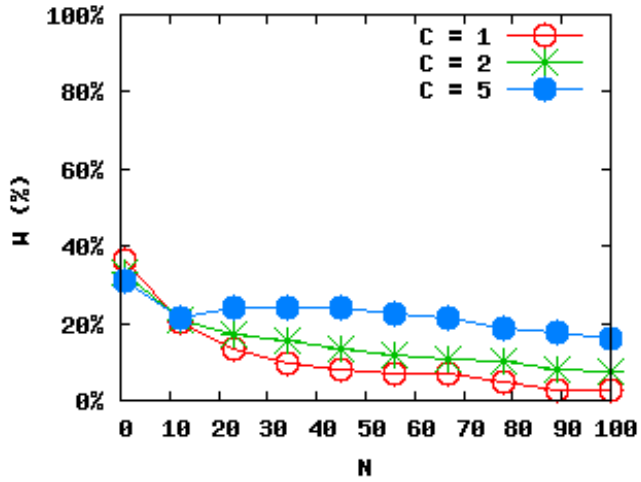

(c) $g = 0.1$ and $r = 0.6$




(d) $g = 0.1$ and $r = 0.4$




(e) $g = 0.9$ and $r = 0.6$




(f) $g = 0.9$ and $r = 0.4$

# Optimal $N^*$ for perfect diagnosis ($r = 0.6$)

| $g$ | 0.1 | | | | |
|---|---|---|---|---|---|
| $C$ | 1 | 2 | 3 | 4 | 5 |
| $N^*$ | 13 | 31 | 90 | 120 | 250 |
| $N_F$ | 5 | 19 | 71 | 111 | 245 |

| $g$ | 0.9 | | | | |
|---|---|---|---|---|---|
| $C$ | 1 | 2 | 3 | 4 | 5 |
| $N^*$ | 200 | 300 | 500 | 1000 | 1700 |
| $N_F$ | 12 | 36 | 84 | 219 | 459 |

# Outline

# Experimental Setup

## Programs

- Siemens set of programs
  - 7 programs with several (single fault) faulty versions
  - O(100) LOC
  - O(1000) test cases
- GNU gcov to obtain the observation matrix

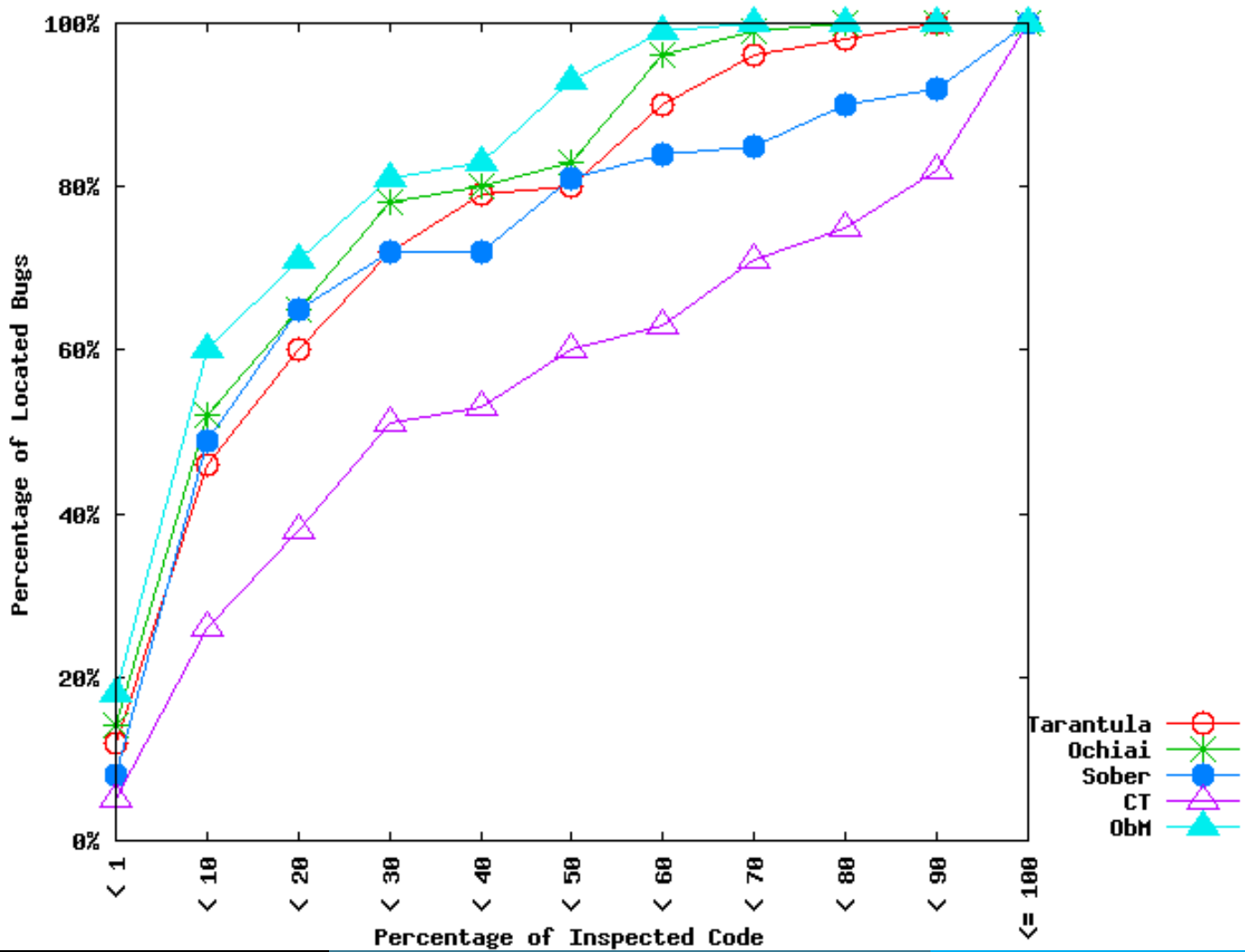
## Evaluation Metric

- Percentage of code that needs to be inspected

$$Effort = \frac{\text{position of fault location}}{LOC}$$

# Experimental Results

## Cumulative Percentage of Located Faults



# Outline

# Conclusions

- Fault localization approach
  - Uses abstraction of program traces to generate a (dynamic, sub-) model
  - The set of traces for pass/fail executions is used to reason about the observed failures
- Set of candidates also contains multiple-fault explanations
- Theoretically, given sufficient test cases are available, this approach will reveal the true faulty state
- Results using the Siemens set have shown that our approach outperforms other state-of-the-art approaches

# Future Work

- Study the diagnostic performance for multiple-fault programs
- Study the possibility of engaging several developers to find the faults
- Reducing the hitting set algorithm complexity
  - STACCATO is under development
- Apply to other (real) programs (e.g., space)

?

For more info:

- `http://www.st.ewi.tudelft.nl/~abreu`
- email: r.f.abreu@tudelft.nl