Spectrum-Based Fault Localization Using Fault Triggering Model to Refine Fault Ranking List

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SUMMARY Spectrum-based fault localization (SFL) is a lightweight approach, which aims at helping debuggers to identity root causes of failures by measuring suspiciousness for each program component being a fault, and generate a hypothetical fault ranking list. Although SFL techniques have been shown to be effective, the fault component in a buggy program cannot always be ranked at the top due to its complex fault triggering models. However, it is extremely difficult to model the complex triggering models for all buggy programs. To solve this issue, we propose two simple fault triggering models (RIPRα and RIPRβ), and a refinement technique to improve fault absolute ranking based on the two fault triggering models, through ruling out some higher ranked components according to its fault triggering model. Intuitively, our approach is effective if a fault component was ranked within top k in the two fault ranking lists outputted by the two fault localization strategies. Experimental results show that our approach can significantly improve the fault absolute ranking in the three cases.

key words: fault localization, software debugging, testing

1. Introduction

Debugging play a key role in software life cycle to improve software quality. A data from the Cambridge University shows total estimated cost of debugging is $312 billion per year in all the world, and programmers spent half of their time in debugging [1]. A general debugging work includes fault detect, localization and fixing. Therefore, a nice fault localization technique can help development groups reduce financial budgets and human resources. According to root causes, faults can be classified into three disjoint types: Semantic faults, Concurrency Faults, and Memory Faults [2]. Tan et al. perform a study for fault characteristics in open source software, they found semantic faults are the dominant root cause of failures. As software evolves, semantic faults increase, and memory-related faults decrease. Therefore, they called for more research effort to address semantic bugs [2]. However, automatic fault localization for Semantic Faults is difficult due to semantic faults are related with requirements or programmers intentions.

Spectrum-based fault localization technique (SFL) is the use of test results and various program spectra collected from the testings to measure the likelihood of a program entity being a fault [3]. SFL techniques have gained much popular due to lower computational overhead and high scalability. However, are SFL can really help programmers localize root cause of failures in reality? Recently, researchers perform some empirical studies or survey researches to try answer this questions, such as [4]–[7]. Despite their differences, they all highlight SFL should improve accuracy and support fault understanding to improve its usefulness.

In previous studies, some researchers focused on proposing different SFL techniques to improve accuracy of fault localization with aid of relationship among components. Zhang et al. [8] highlighted that a fault may propagate a series of infected program states before triggering a failure. They used edge profiles to model infected program states, and by associating basic blocks with edges, the suspiciousness scores for each component was calculated. Baah et al. [9], [10] applied casual inference to fault localization, and a linear model was built on program dependency graph to estimate the causality of failures of a given program component. Wang et al. [11] proposed a SFL approach combined with fault context of program spectrum.

Different from previous works, we propose a SFL technique using fault triggering model to further refine fault ranking list for a SFL technique. The above mentioned approaches are also easily combined into our approach. Our idea behind this is that we can refine the fault ranking list via ruling out some components ranked higher if we know that they follow which fault triggering model. The fault triggering model is discussed in detailed in Sect. 4. There exist two fault triggering models, called RIPRα and RIPRβ. Informally, if a fault triggering model belongs to RIPRα, then the root fault(s) is covered in all failed executions for a specific test suite, otherwise, it belongs to RIPRβ. Although our idea seems to be obvious and simple, it is helpful to refine the fault ranking list. For example, we assume a component c_i in a single-fault program, which the fault triggering model clearly belongs to RIPRα, is ranked at the top in a list of suspicious components generated by a SFL technique. If we know c_i is not covered in a failed execution, it is easily to know that c_i can view as a fault-free component based on Reachability, Infection, Propagation, and Revealleability (RIPR) model [13]. Therefore, we could exclude c_i from the fault hypotheses set using this information. We summarize explicitly the simple but essential idea into two different
fault triggering models, which should be considered in guiding programmers to localize fault. Based on the characters of the two fault triggering models, different fault localization strategies were proposed.

In summary, this article makes the following contributions:

- two fault triggering models are proposed based on RIPR.
- two strategies using fault triggering model to refine fault ranking list were proposed.
- an empirical evaluation of our approach on 129 program versions from the SIR dataset for three different fault localization scenarios, and the results are promising.

This paper is organized as follows: In Sect. 2 gives a motivation example to illustrate our idea. Section 3 describes some preliminaries for our approach. Section 4 presents fault triggering model and two fault localization strategies, followed by an empirical evaluation in Sect. 5 and related works in Sect. 6. Section 7 concludes this paper and give some future works.

2. Motivation Example

In this section, we illustrate our research motivation with an example shown in Fig. 1, which is a program segment excerpted from program schedule v2 [14]. The program section manages a process queue. It first calculates the index of the target process and then moves the target process in the priority queue. The buggy program segment contained a bug in line 2, which should get the index of the target process which is accidentally written as count = block_queue->men_count + 1. Columns 1 to 3 shows the statement numbers, program segment, and the corresponding number of basic blocks. Columns 4 to 11 represents t1 − t8, respectively. The program spectrum is represented in the column, and indicates whether the corresponding block is executed in the test case (‘1’ for executed, ‘0’ for not executed). The result of the test is given in the bottom row, where ‘1’ indicates failure and ‘0’ indicates success.

As we know, SFL techniques, such as Dstar, focus on independently calculating the suspiciousness of each component and ranking all components based on their suspicious scores. In our example, b2 has the highest suspiciousness among the four basic blocks, which is higher than the actual fault b3. In this case, it is difficult to lower the ranking for b3 or improve the ranking for b2 underlying the assumptions for those SFL techniques. Due to the example only contains a single fault, we easily to know the fault triggering model is RIPRα, in which the fault(s) triggers failures in all failed tests.

We find that b1 is not executed in failed test t6. Hence, it is easily to infer b1 is non-fault component which can be excluded from the fault ranking list. So, b2, which is the root cause of failures, is the highest ranking. The characteristics for RIPRα and RIPRβ are different, therefore, we adopt different fault localization strategies mentioned as Sect. 4 to perform fault localization.

3. Preliminary

3.1 Definitions

**Definition 1:** \( P = (c_1, c_2, \ldots, c_n) \) is a program, which contains \( n \) components. Components can be statements, blocks, or functions, etc.

**Definition 2:** \( T = (t_1, t_2, \ldots, t_m) \) is a test suite, which contains \( m \) test cases. We divided \( T \) into two groups, \( T_f \) for all failed test cases and \( T_s \) for all successful test cases.

There are many types of mistakes that occur during software development. The following three terms are adopted by IEEE conventions [15].

**Definition 3:** Fault/Bug is a static defect in the software.

**Definition 4:** Failure, which can be observed, is an external, incorrect behavior which does not meet with the software requirements.

**Definition 5:** Error, is an incorrect internal state and can not be observed directly, which is the manifestation of faults/bugs in program execution.

3.2 Spectrum-Based Fault Localization

SFL techniques exploit program spectrum, which includes information about component coverage information in a program executions [16]. Collection of program spectra is a lightweight program analysis approach, and program spectrum provides a dynamic view on behavior of the program [3].

A program spectra can be represented as a binary \( N \times M \) Coverage Matrix \( A \). In matrix \( A, N \) is the number of successful executions and \( M \) is the number of program component which is be instrumented. The result of each program running be collected and stores in a \( N \)-length error detection vector, which also called Result Vector \( e \). In the result vector \( e \), ‘0’ indicates successful and ‘1’ indicates failed. The
Coverage Matrix and Result vector show as Fig. 2. The key for a SFL technique is measurement of suspiciousness based on Coverage matrix and Result vector. There exists several similarity metric may use to compute suspiciousness [17]. Given an input \((A, e)\), the coverage information as blow be calculated.

- \(n_{00}(s)\) is the number of successful runs that do not cover a component \(s\).
- \(n_{01}(s)\) is the number of failed runs that do not cover a component \(s\).
- \(n_{10}(s)\) is the number of successful runs that cover a component \(s\).
- \(n_{11}(s)\) is the number of failed runs that cover a component \(s\).
- \(n_{s}()\) is total number of test cases that cover a component \(s\).
- \(n_{,s}()\) is total number of failed test cases.

Four similarity metrics of well-known fault localization techniques: Jaccard [18], Tarantula [19], Ochiai [18], and Dstar [20], are defined as below:

\[
\text{Jaccard}(s) = \frac{n_{11}(s)}{n_{01}(s) + n_{11}(s)} \tag{1}
\]
\[
\text{Tarantula}(s) = \frac{n_{o0}(s) \times n_{11}(s)}{n_{11}(s) \times n_{11}(s) + n_{1,1}(s) \times n_{11}(s)} \tag{2}
\]
\[
\text{Ochiai}(s) = \frac{n_{11}(s)}{\sqrt{(n_{11}(s) \times (n_{1,1}(s)))}} \tag{3}
\]
\[
\text{Dstar}(s) = \frac{(n_{11}(s))}{n_{01}(s) + n_{10}(s)} \tag{4}
\]

### 3.3 Spectra-Based Fault Reasoning

Abreu et al. [21] proposed a multiple-fault localization technique, named BARINEL. The technique used a Bayesian Inference framework to debugging with intermittent faults. A parameter \(h_i\) was introduced to represent the likelihood of a component \(i\) showing a health behavior.

We assume there exist a hypotheses set \(D = \langle d_1, \ldots, d_k \rangle\), which can be computed by Minimum Hitting Set algorithm, such as STACCTO [22]. Each element in \(D\) is a subset of the program components that, when at program failure, can explain the faulty behavior.

After program testing, similarly as SFL, Coverage Matrix \(A\), and Result vector \(e\) were collected. Each element \(d_i\) in \(D\) are ranked based on their likelihood of being the correct diagnosis. This probability is defined as Formula (5):

\[
P(d_k|\text{obs}) = p(d_k) \cdot \prod_{\text{obs}, \text{obs}} \frac{p(\text{obs}|d_k)}{p(\text{obs})} \tag{5}
\]

where \(\text{obs}_i\) is the row \(A_{1*}\), which represent a program spectrum collected by running test \(t_i\), and \(\text{obs}_i < \text{obs}\). The \(p(d_k)\) is a priori probability of the element \(d_k\), defined as Formula (6):

\[
P(d_k) = p^{\|d_k\|} \cdot (1 - p)^{|D| - |d_k|} \tag{6}
\]

where \(p\) is a priori probability of a component being a fault, and \(P(\text{obs}|d_k)\) represents the probability of \(\text{obs}_i\) if the component \(d_k\) was the actual fault, and is given by Formula (7):

\[
p(\text{obs}|d_k) = \begin{cases} 0, & \text{if } \text{obs}_i, e_i, \text{ and } d_k \text{ are inconsistent} \\ \xi, & \text{otherwise} \end{cases} \tag{7}
\]

The denominator \(p(\text{obs})\) is a normalizing term that is equal for all \(d_k \in D\) needs not to be computed for ranking purposes.

### 3.4 Assumptions

**Assumption 1.** The output of a program \(P\) is deterministic.

Namely, the program \(P\) always produces the same result in different executions given the same input value.

**Assumption 2.** A program failure occurred always meet with RIPR model.

SFL techniques are characterised by measuring suspiciousness based on Coverage vector of component and its Result vector. Therefore, a SFL does not typically find fault if the fault can not be reached in program executions, such as Missing code faults, variable declaration faults and et al., which have no faults be reached during program executions, although those cases can still be interpreted by RIPR model.

**Assumption 3.** There exist a test oracle that determines the status of a test execution for program \(P\), i.e., “successful” or “failed”.

Constructing the test oracle is a difficult, independent research problem. Assumption 3 is made to simplify the approach. Given a test oracle, our approach may be fully automated to collect Coverage Matrix and Result Vector.

**Assumption 4.** There exist many failed test cases in tests.

In our approach, we require many different failed program spectra to rule out some components ranked highly iteratively. Our approach can not refine fault ranking list if there exist only one failed program spectrum.

### 4. Our Approach

#### 4.1 RIPR Model

Offutt and Morell propose independently Fault&Failure
Model in which they point a failure to be observed must follow three necessary conditions, which published as different notations [23], [24]. Recently, Li and Offutt [13] extend the Fault&Failure Model, and they highlight there exist four necessary conditions, namely Reachability, Infection, Propagation and Revealability (called RIPR model). In Fig. 3, the RIPR model was shown. The four conditions are defined as follows:

- **Reachability:** The program component containing the fault(s) must be reached.
- **Infection:** The components must infect the internal state of the program.
- **Propagation:** The infected state must propagate, causing some output to be incorrect.
- **Revealability:** The tester must observe part of the incorrect portion of the program state.

We though an example, which was shown in Fig. 4, to illustrate the RIPR model. The buggy program contains a single fault, and the fault is that it should start searching at index 0 instead of index 1, as is the necessary for arrays in Java language. In software testing community, the purpose is choosing input data to trigger fault and cause failure. In the example, for inputting array [1, 2, 0] correctly get result 1, while inputting array [0, 2, 3] incorrectly get result 0. In the two cases the fault is both reached. Although both of these cases result in some errors, only the second case the fault triggers a failure. To understand those errors, we need to identify the state for the program, which can represent as \{(x, count, i), PC\}, where PC is program execution counter. Inputting array [1, 2, 0], \{(x=[1,2,0], count=0), PC=if\} represents the program state where the program executes at if statement on the first iteration of the loop. Notice that this state is an error due to the value of count correct coincidentally. Therefore, the error does not propagate to the program output. For inputting array [0, 1, 2], similarly, the state at if statement on the first iteration of the loop is \{(x=[0,1,2], count=0), PC=if\}. The error propagate to the output and a failure is revealed by the Test Oracle Strategies.

Due to our purpose of fault localization, we can easily infer the fault location(s) and fix it if we know the RIPR model. However, it is difficult to model error state and determine whether it is error, and the propagation of infected error for the complex program dependency. Therefore, we only focus on measuring the suspiciousness for each program component in SFL techniques. According to RIPR model, for failed spectra, root cause(s) of failures must be triggered and revealed. Considering the two necessary conditions, we can define two different fault triggering model: RIPRα model and RIPRβ model.

4.2 Fault Localization Strategy for RIPRα Model

As mentioned in the above section, a failed running for a buggy program must be satisfied with RIPR model. Therefore, a failed execution for a buggy program must be reached the root fault, infected states, propagated the error states, and revealed by test oracle strategies. That is to say, a failed program spectrum must be contained the root fault(s), and a successful execution may possibly covered the root fault(s), but not satisfied the other necessary conditions which make it correct coincidentally [25].

Based on RIPR model, each component in each failed program spectrum is probably root fault. Therefore, for a failed test case \(T_f\), we can defined suspicious components as Formula (9).

\[
\text{suspicious}(T_f) = \{c_j | c_j \in \text{getSpectrum}(T_f)\}
\]  

(9)

where \(T_f\) is a failed test case, \(\text{getSpectrum}(T_f)\) get a set of components which covered by a program spectrum by running a failed test case \(T_f\).

For a failed test suite, we define suspicious components set which covered by all failed test cases as Formula (10).
Algorithm 1 Fault Localization for RIPRβ

Input: Spectrum Matrix A, test result e, suspiciousness metric ρβ;
Output: fault ranking list Dα;
1: \( A_f \leftarrow filterPassA(A, e) \)
2: for each i in \(|e|\)
do
3: \( \text{Suspicous}_i \leftarrow getComponent(\text{A}_f) \)
4: end for
5: \( \text{Suspicous}_α = \bigcap_i \text{Suspicous}_i \)
6: \( A_α, e_α \leftarrow filter(A, e, \text{Suspicous}_α) \)
7: for j = 0 to \( |\text{Suspicous}_α| \)
do
8: \( \text{setValues}(n_00(i), n_01(i), n_10(i), n_{11}(i)) \);
9: \( S(i) \leftarrow ρβ(n_00(j), n_01(j), n_10(j), n_{11}(j)) \);
end for
10: \( D_α \leftarrow sort(S) \);
11: return \( D_α \);

Table 1 Spectra gathered when running test-suite for RIPRα

<table>
<thead>
<tr>
<th>T</th>
<th>c1,4</th>
<th>c2</th>
<th>c3,5</th>
<th>c6</th>
<th>e</th>
</tr>
</thead>
<tbody>
<tr>
<td>( t_1 )</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>pass</td>
</tr>
<tr>
<td>( t_2 )</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>pass</td>
</tr>
<tr>
<td>( t_3 )</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>fail</td>
<td></td>
</tr>
<tr>
<td>( t_4 )</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>fail</td>
<td></td>
</tr>
<tr>
<td>( t_5 )</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>pass</td>
<td></td>
</tr>
</tbody>
</table>

Table 2 Filtered spectra for RIPRα

<table>
<thead>
<tr>
<th>T</th>
<th>c1,4</th>
<th>c2</th>
<th>c6</th>
<th>e</th>
</tr>
</thead>
<tbody>
<tr>
<td>( t_3 )</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>fail</td>
</tr>
<tr>
<td>( t_6 )</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>fail</td>
</tr>
</tbody>
</table>

\[
\text{Suspicous}_α(T_j) = \bigcap_{i \in T_j} \text{Suspicous}_i(t_i) \quad (10)
\]

In RIPRβ model, the components covered in all failed tests can be viewed as suspicious fault(s). The fault localization strategy for RIPRβ is described in Algorithm 1. Table 1 shows an example program spectrum collected by some test executions. Considering some components have same coverage information, we group them such as \( c_{1,4} \). In the following, we illustrate our approach using the example.

Based on RIPRα model, we firstly generate failed spectra by filtering successful program spectra, which was shown as Table 2. Then we get components belonging to fault triggering model RIPRα. In the example, \( \{c_{1,4}, c_2, c_6\} \) that are all triggered in all failed tests belong to RIPRα. Although those components belong to the same fault triggering model, their suspiciousness are different. We can use SFL techniques directly to compute suspiciousness for each component and rank them.

4.3 Fault Localization Strategy for RIPRβ Model

Based on RIPR model, each component in each failed program spectrum is probably root fault. The suspicious components for single-fault programs defined as above section. However, for some programs contained multi-faults, all faults are not triggered in every failed test case. In this scenario, we should exclude two groups in the suspicious set: components that all be covered in all failed spectra and all components that are never covered by all failed spectra.

In practice, components that all be covered in all failed spectra belong to fault triggering model RIPRβ, which be defined as Formula (9). Components that are never covered by all failed spectra can be defined as Formula (11), (12). We define components belonged to fault triggering fault RIPRβ as Formula (13).

\[
C_0(T_j) = \{c_j | c_j \notin getSpectrum(T_j)\} \quad (11)
\]

\[
C_0 = \bigcap_{t_i \in T_j} C_0(t_i) \quad (12)
\]

\[
\text{Suspicous}_β(T_j) = C \setminus C_0 \setminus \bigcup_{t_i \in T_j} \text{Suspicous}(t_i) \quad (13)
\]

In RIPRβ model, those components which are not covered by all failed tests can be viewed as suspicious fault(s). Table 3 depicts an example program spectrum collected by the test runs. Table 4 give the result of filtering spectra for RIPRβ. Based on RIPRβ model, from the first row it easily know \( c_1 \) could be one of the faults due to the failure can only be caused by at least one faulty component. Similarly, component \( c_2 \) also can be inferred it is probably be among the bug components. Therefore, \( \{c_1, c_2\} \) is only possible fault diagnosis. In practice, there exist a lot of diagnosis candidates such as \( \{c_1, c_2\} \) can explain program failures. We can use STACCATO algorithm to generate minimal candidates, i.e., candidates that can not be subsumed by any other lower cardinality candidate [22]. Furthermore, we sort those candidates based on their probability of being the correct diagnosis. Therefore, we can use Spectra-based fault Reasoning technique directly to perform fault localization for RIPRβ scenario. Fault localization framework for RIPRβ model is described in Algorithm 2.

According definition of fault triggering model RIPRβ, multi-fault programs can be divided three cases:

- **Case 1**: all faults are covered in all failed program spectra, which can be viewed as RIPRα,
- **Case 2**: some faults are covered in all failed program spectra, others are not, which can be viewed as combination of RIPRα and RIPRβ. In this, we can combine the two strategies to perform fault localization.
- **Case 3**: all fault(s) are not triggered in every failed test
Table 5: Subjects used for empirical studies

<table>
<thead>
<tr>
<th>Program</th>
<th>LOC</th>
<th>BBs</th>
<th>Vers</th>
<th>Testcases</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>print_token</td>
<td>478</td>
<td>122</td>
<td>5</td>
<td>4130</td>
<td>Lexical analyzer</td>
</tr>
<tr>
<td>print_token2</td>
<td>399</td>
<td>135</td>
<td>9</td>
<td>4115</td>
<td>Lexical analyzer</td>
</tr>
<tr>
<td>replace</td>
<td>512</td>
<td>153</td>
<td>26</td>
<td>5542</td>
<td>Pattern matcher</td>
</tr>
<tr>
<td>schedule2</td>
<td>292</td>
<td>73</td>
<td>8</td>
<td>2650</td>
<td>Priority scheduler</td>
</tr>
<tr>
<td>tcas</td>
<td>301</td>
<td>77</td>
<td>8</td>
<td>2710</td>
<td>Priority scheduler</td>
</tr>
<tr>
<td>tot_inf</td>
<td>141</td>
<td>23</td>
<td>36</td>
<td>1608</td>
<td>Aircraft control</td>
</tr>
</tbody>
</table>

Algorithm 2 Fault Localization for RIPRβ

```
Input: Spectrum Matrix A, test result e;
Output: fault ranking list Dβ;
1: Af ← filterPass(A, e);
2: for each i in |Af| do
3:   Suspicousi ← getComponent(Af)
4:   C0 ← C \ Suspicousi
5: end for
6: C0 = \bigcap_{i\in|Af|} C0
7: Suspiciousβ = C \ C0 \ \bigcap_{i\in|Af|} suspicousi
8: Af, eg ← filter(A, e, suspicousβ)
9: Dβ ← BARINEL(Af, eg);
10: return Dβ;
```

4.4 Discussion

In this section, we discuss the two fault localization strategies respectively. RIPRα strategy would lead to the best for single-fault programs. We use the following theorem to verify this conclusion.

Theorem 1: For single-fault programs, given Coverage Matrix A and Result vector e, the suspicious component ranking list outputted by RIPRα is the most superior theoretically.

Proof 1: For a single-fault program, the single fault component must be covered in all failed tests. On the contrary, if a component which do not covered once in a failed execution, the component can be viewed as non-fault component due to those components can not explain all program failures. This can imply that for a remaind component e, n11(e) is equal to n01, and n00(e) is equal to 0. Therefore, D\text{star} can be written as:

\[
\rho_D^{\text{top-10}}(e) = \frac{1}{n_{10}(e)}
\]  

As we have already ruled out all components whose n_{11} < n_{01}, the rank list outputted by our approach is optimal.

If a buggy program belongs to RIPRβ, there no fault be covered in all failures. Therefore, a single suspicious component can not explain all failures. In this scenario, a minimal-hit set that can explain all failures is better choose than single component.

As mentioned above, if a program is single-fault program, we could use RIPRα strategy to perform fault localization, and get an optimal solution. However, Although single-fault programs are the majority, there are still multiple fault programs in practice [27]. But above all, we don’t know if a program is a single-failure or multiple-failure program, and not to mention what kind of fault trigger model it belongs to. Thence, we could not apply the two strategies directly for a buggy program. Let us look closer at the ranking list outputted by the two strategies, the two ranking lists are disjoined. Therefore, we can combine the two fault ranking list to perform fault localization.

Recently, Kochhar et al. pointed that 98% of practitioners consider a SFL technique is useful only if it outputted fault component(s) within the top-10 in fault ranking list [5]. Inspired by this view, there exist many heuristic methods to guide the combination of the two strategies. For example, we could first check top 5 outputted by RIPRα strategy, if we can not find the root fault, then we find next top 5 outputted by RIPRβ strategy. If we cannot find fault component(s) in the two strategies, we recommend that programmers switch to other fault localization techniques for debugging.

In short, if fault component(s) is ranked within the top k in any two ranking lists, it is very meaningful to our approach. Additionally, if we find a fault component in the ranking list outputted by RIPRβ strategy, we easily to infer that this is a multi-fault program, which is very important to programmers. This information can guide programmers to perform their next work.

5. Empirical Evaluation

We built a SFL prototype tool, called TRIGGER, based on fault triggering model to refine fault ranking list, and we present an empirical evaluation for TRIGGER. In particular, we search for answers to the following three research questions:

- **RQ1** What is the effectiveness of TRIGGER on RIPRα?
- **RQ2** What is the effectiveness of TRIGGER on RIPRβ?
- **RQ3** What is the effectiveness of TRIGGER on uncertain fault triggering model?

5.1 Subject Programs

In our experiments, we used 7 C programs from SIR as experiment objects [14]. Those programs contain tokens, tokens2, replace, tot_inf, schedule, and schedule2. Table 5 shows the detailed characteristics of these programs. To meet Assumption 3, we created a fault-free version for each program and constructed a test oracle to determine the testing result of program versions. Columns 2 to 3 shows the number of uncommented code lines and basic blocks for these programs the 4th column gives the number of buggy versions for each program, the 5th column gives the number of test cases for each program, and the last column describes detailed information for each program.
There exist 132 versions in the suites, and there exist program versions that are seeded with bugs in variable declarations, which do not meet Assumption 2. Due to the instrumentation can not reach these declarations, we denote the directly infected block or an adjacent executable block as the location of fault to reflect the effectiveness of our approach. We excluded the two program versions print_tokens4, print_tokens6 due to they are identical to the bug-free version. We ignored schedule2_9, because their test results are all successful, namely, they have no failed test case. In total, the subjects of our experiment included 129 versions of the Siemens suite from SIR [14].

5.2 Effectiveness Metric

Effectiveness metrics are an important way to perform accurate and objective comparisons. There are two main metrics: PDG-based metric [32], and Ranking-based metric [20], which used to measure fault localization quality in the field.

Parnin and Orso suggested that SFL techniques should focus on improving absolute ranking rather than percentage rank. Recently, Wang et al. proposed a improvement metric to measure the absolute ranking improvement [11]. Let \( B \) be the fault absolute ranking outputted by a SFL technique for a buggy version, and \( A \) be the fault absolute ranking outputted by our approach for the same program version. The effectiveness metric can be defined as Formula (15):

\[
\text{Impr}_{TIR}^{SFL}(A, B) = \begin{cases} 
0, & \text{if } B = 0 \\
\frac{B - A}{B} \times 100\%, & \text{Otherwise} 
\end{cases}
\]  

(15)

In our experiment, we adopt the Effectiveness metric as our evaluation metric. In this research, our goal is to improve the fault absolute ranking. Therefore, if \( B = 0 \), we have no room to improve because it has been ranked at the top. In this case, we believe the improvement is 0%. We assume that our approach is 100% improved to compare with a SFL technique if fault component is ranked at the top. Therefore, we assign the index of fault ranking list beginning at 0 (\( \frac{112}{1} \times 100\% = 100\% \)). For example, if a SFL ranked the root cause at 20 for a buggy program and our approach ranked it 17, we can say our improvement is \( \frac{19-16}{19} \times 100\% = 15.8\% \).

5.3 Empirical Results

To study the effectiveness of our approach, we answer our research questions by performing a set of experiments. Pearson et al. highlight that all SFL techniques are equally good for real faults. Therefore, we choose Dstar as a benchmark, and we have reasons to believe that, our approach is effective compared with other SFL techniques if our approach is effective compared with Dstar. We divide the subject programs into two groups by fault triggering model: \( \text{RIPR}_a \) and \( \text{RIPR}_b \). For \( \text{RQ1} \), we use programs which fault triggering model belong to \( \text{RIPR}_a \) as the experimental subject and perform \( \text{RIPR}_a \) fault localization strategy to locate the fault.

For \( \text{RQ2} \), we use programs which fault triggering model belong to \( \text{RIPR}_b \) as the experimental subject and perform our \( \text{RIPR}_b \) fault localization strategy to locate fault. Due to there exist fewer programs to meet \( \text{RIPR}_b \) in the Siemens programs, we add an additional experiment for \( \text{RIPR}_b \). However, in real programs, we do not know which fault triggering model belong to in a buggy program. Therefore, for \( \text{RQ3} \), we use all the Siemens programs as experimental subjects and combined the two strategies to locate fault(s).

5.3.1 RQ1: \( \text{RIPR}_a \) Programs

In this section, our goal is to compare the effectiveness of our \( \text{RIPR}_a \) with Dstar. We first investigate programs where fault triggering model belong to \( \text{RIPR}_a \), and there exist 122 program versions including 117 single-fault programs and 5 multi-fault programs. We run Dstar and our approach using \( \text{RIPR}_a \) fault localization approach independently and collect the two fault ranking lists.

We use the Effectiveness metric mentioned above to estimate the effectiveness for our approach. We calculate the Effectiveness metric based on the two fault ranking list outputted by our approach and Dstar. Figure 5 shows the experiment results. In the 122 fault versions, 10 faults of program versions are ranked at the top in fault ranking list outputted by Dstar technique, and our approach performs better than Dstar tool on 69 versions. The results show that no program versions perform worse than Dstar. In those 69 versions, the average improvement is 49.5%, and it is worth mentioning that the fault component of 8 buggy program versions are ranked highest in the fault ranking list.

5.3.2 RQ2: \( \text{RIPR}_b \) Programs

In this section, we firstly use 7 multi-fault programs which fault triggering model belonged to \( \text{RIPR}_b \) to evaluate our approach effectiveness. Our objective is to compare \( \text{RIPR}_b \) with Dstar. In our \( \text{RIPR}_b \) context, we wish the Effectiveness evaluation is independent for the number of faults \( F_n \) in the buggy programs to perform an unbiased effectiveness evaluation for the effect of \( F_n \). To do this, we rank
for each component in candidate diagnosis \(d_i\), outputted by \textit{TRiGGER}, which contained multi-components based on suspiciousness metric \(Dstar\). For example, consider a buggy program contained 5 components with the following fault report \(D = < d_1 = \{c_2, c_3\}, d_2 = \{c_3, c_1, c_4\}\), while \(c_2\) and \(c_3\) are root faults. To better compare with \(Dstar\), we rank each component in \(d_1\) and \(d_2\), and get a ranking list similarly as \(Dstar\), such as \(< c_5, c_2, c_1, c_3, c_4 >\). In the ranking list, we use highest absolute ranking among the multi-fault components as the fault absolute ranking to compare with \(Dstar\). In the example, the fault absolute ranking is 1 (due to absolute ranking begin with 0).

Table 6 shows the effectiveness improvement in fault absolute ranking for the 7 program versions which fault triggering model belong to \(RIPR_{\beta}\) model. For example, for \textit{tcas-v10}, which contains 2-faults, our approach ranks the fault component at \textit{top-3}, while \(Dstar\) ranks the fault component at \textit{top-5} (Attention here, the index of fault ranking list starts from 0). Therefore, for our \textit{Effectiveness metric}, the improvement is 50%.

Table 7 shows the additional program versions for \(RIPR_{\beta}\) empirical studies. From Table 6, except for \textit{schedule2v7}, we find that our approach is effective to improve the fault absolute ranking compared with \(Dstar\). And for \textit{schedule2v7}, one of faults was ranked at the highest by \(Dstar\) technique, hence, there is no room for improvement. It is worth mentioning that fault ranking of the three program versions is improved to the highest ranking.

Considering there exists fewer buggy programs which belong to \(RIPR_{\beta}\), we add an additional experiment for \(RIPR_{\beta}\). We extend the subject programs with program versions where we can activate arbitrary combinations of multiple faults. We limit the scope to a selection of 83 faults from the 129 program versions, which the selection criteria is that the fault being attributable to a basic block, to enable unambiguous evaluation. We select fault combinations randomly, and the detailed information is shown in Table 7.

In Table 7, \(C\) is the number of injected faults (cardinality), \(N\) is the number of program versions which are randomly injected with \(C\) faults which were combined from the 83 faults, and \(N_{RIPR}\) is the number of program versions belonged to \(RIPR_{\beta}\). As mentioned as above Sect. 4.3, for those multi-fault programs, we exclude programs that belong to \textit{Case 1} and \textit{Case 2}. There are total (100) program versions that belong to \(RIPR_{\beta}\).

We compare the fault absolute ranking outputted by our approach with \(Dstar\) in terms of \textit{Effectiveness metric}. The result was shown in Fig. 6. Experimental results show that there exist 65 versions perform better than \(Dstar\) (65%), 9 versions perform worse than \(Dstar\) (9%), and 26 versions have no improvement (26%). In total 100 versions, the average improvement is 38.37%. Considering we adopt different suspiciousness metrics for those program versions, there exist a few versions are worse than \(Dstar\). The result reconﬁrm our approach for \(RIPR_{\beta}\) is more effective than traditions \(Dstar\) to improve absolute ranking.

5.3.3 RQ3: Uncertain Type Programs

In practice, we do not know which fault triggering model a program belong to. Therefore, we cannot apply directly the \(RIPR_{\alpha}\) strategy or \(RIPR_{\beta}\) strategy. We are easy to find that the set of the fault ranking lists outputted by \(RIPR_{\alpha}\) and \(RIPR_{\beta}\) are disjoined. Hence, we could combine the two fault localization strategies to perform fault localization for the program which do not know its type of fault triggering model. Specifically, we run the two fault localization strategies independently and obtain two suspicious regions: one for \(RIPR_{\alpha}\) strategy and the other for \(RIPR_{\beta}\) strategy. Then, we compute the suspiciousness score for each component in the two suspicious set and ranking the two suspicious set in descending order by their suspiciousness scores independently.

In this section, our goal is to compare the effectiveness of our approach for programs contained uncertain number faults. We run our approach based on the following localization strategy: We check top 7 outputted by \(RIPR_{\alpha}\) strategy firstly, then try to check the top 3 outputted by \(RIPR_{\beta}\) strategy if they can not find root cause of failures.
In order to compare our results, we take the highest fault absolute ranking as the result of our approach. For example, program `icas-v10` contains two faults, a fault ranked at `top-3` in a fault ranking list, another ranked at `top-4` in the other fault ranking list. We take `3` as our absolute ranking.

Table 8 presents the effectiveness comparison of `Dstar` and our `TRiGGER`. Columns `N_{Dstar}` and `N_{TRiGGER}` show the number of programs for which the root cause was ranked at `top X` based on `Dstar` and `TRiGGER`. The column `Improve` shows the improvement between `Dstar` with `TRiGGER`, which can be calculated as:

\[
    \text{Improve} = \frac{N_{Dstar} - N_{TRiGGER}}{N_{Dstar}} \times 100\% \quad (16)
\]

Let us look closely at Table 8. One observation is that the improvement in the number of programs for which the root cause is ranked within `top k`. Specifically, for `Dstar`, 15 fault components were ranked at the top, while 25 fault components were ranked at the top by our approach, which improvement is 66.7%. Recently, Xie et al. found that the accuracy of `SFL` still matters, and an inaccurate `SFL` result would mislead programmers and is not helpful in terms of improving the efficiency of debugging [6]. Therefore, the result of our approach makes sense to improve the absolute ranking at the top. Additionally, our approach does not show a significant improvement as `X` increases. For example, the improvements for the absolute ranking at `top-2`, `top-4` and `top-9` are 30.2%, 13.8%, and 30.2%, respectively. We conjectured that this result is due to the characteristics of `SFL`, which suggests that some programs can further improve the absolute ranking if the `SFL` is effective for those programs. This observation inspires further research to improve automated fault localization techniques.

### 5.4 Threats to Validity

We make four assumptions in Sect. 3.4 for our approach. In Assumptions 3, we assume there exists a test oracle that determines the status of a test execution for programs. Test oracle is easy to understand, and it is only made to simplify our approach. Therefore, we only consider the rest three Assumptions of threats to validity.

In Assumption 1, we assume the output of a program is deterministic. In practice, if a program is concurrent, the program would produce different results in different executions given the same input value. Therefore, if a program does not meet Assumption 1, it is difficult to reproduce software failure and localize the fault.

Despite `RIPR model` can interpret all failures, some failures are not indeed satisfied, such as missing code, variable declaration faults. For those variable declaration faults, the instrumentation can not reach these fault locations in program executions. We use directly infected block or an adjacent executable block as the location of the faults to evaluate the effectiveness of our approach. However, for missing code faults, we have no good idea to perform testing and fault localization, which is opening questions in our community.

In Assumption 4, we assume there exist many failed test cases in program testings. Considering cost of testing, there are not always a large number of failed test cases in reality. If there exist one failed tests, our approach have not chance to improve the fault absolute ranking. However, the Assumption 1 is easily checked. If there exist one single fault tests, we can switch to other fault localization to perform fault localization continuously.

### 6. Related Works

Several `SFL` approaches have been proposed, such as `Tarantula` [19], `Ochiai` [18], `Dstar` [20], `SOBER` [28] and others (e.g., [33]–[36]). Experimental results shown that `SFL` techniques can help programmers to perform program debugging [29].

However, are `SFL` actually helping programmers? To answer this question, some user studies have been performed. Their experimental results indicated a `SFL` tool is useful only if the fault component(s) is ranked within `top k` [5], [7], [26]. Especially, Pearson et al. highlighted that `SFL` results on programs seeded by artificial faults is not predictive for real faults and there do not exist a `SFL` technique outperform other `SFL` techniques in all buggy programs [12]. Wang et al. [11] pointed out a `SFL` technique can further improve the fault absolute ranking if the `SFL` technique is effective for a buggy program. We believe that further improving a fault absolute ranking is essential to improve the usefulness of the `SFL` techniques.

Abreu et al. [30] proposed a fault localization framework, called `DEPUTO`, which framework is also used to refine the fault ranking list by filtering out the components which can not explain the observed failures. They combined `SFL` with a model-based debugging approach based on abstract interpretation. Different their approach, our approach only use a `SFL` technique based fault triggering models.

Xie et al. proposed a refinement approach to improve the accuracy of `SFL` techniques [31]. They divided program statement into two groups: unsuspicious group and suspicious group. The suspicious group contains the statements which have shown up at least once in failed spectra. On the contrary, the unsuspicious group contained the statements have not shown up in any failed program spectra. Although their approach is similar to our approach, their approach is different from ours. We propose the two fault localization strategies which is based on different fault triggering models, and not the two groups. heir suspicious group also can be apply the two fault localization strategies to refine the fault absolute ranking list.
Our approach is also different from Set-union and Set-intersection [32]. They use a single failed spectrum and all successful program spectra as an input in the two approaches. For Set-union method, they focused on the program component that is executed by the failed test but not by any of the successful tests. For Set-intersection method, they excluded the component that is executed by all successful tests but not by the failed test. Obviously, if there exist a single failed spectrum, it does not satisfy Assumption 4. In this scenario, our approach does not improve fault absolute ranking. On the contrary, if there exist many different failed spectra, we can not apply the two approach directly.

7. Conclusion and Future Works

In this paper, we propose a SFL technique using fault triggering model to refine fault absolute ranking list. The intuition is that a fault ranking list outputted by a SFL technique would be confounded by different fault triggering models. The two fault triggering models, called RIPR and RIPRf, were proposed. For the two triggering models, we propose different fault localization strategies to perform fault localization. Experiments were performed to evaluate our approach, and the results are promising.

In our future work, we plan to perform more empirical studies to further evaluate the effectiveness of our approach. Moreover, we plan to perform user study to evaluate the effectiveness for our approach. In the next step, we also plan to apply our approach to program slice spectra to refine the fault absolute ranking list.

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