Spectrum-Based Fault Localization Framework to Support Fault Understanding

Yong WANG††††, Zhiqiu HUANG††††, Yong LI††, RongCun WANG††††, Nonmembers, and Qiao YU††††, Member

SUMMARY A spectrum-based fault localization technique (SBFL), which identifies fault location(s) in a buggy program by comparing the execution statistics of the program spectra of passed executions and failed executions, is a popular automatic debugging technique. However, the usefulness of SBFL is mainly affected by the following two factors: accuracy and fault understanding in reality. To solve this issue, we propose a SBFL framework to support fault understanding. In the framework, we firstly localize a suspicious fault module to start debugging and then generate a weighted fault propagation graph (WFPG) for the hypothesis fault module, which weights the suspiciousness for the nodes to further perform block-level fault localization. In order to evaluate the proposed framework, we conduct a controlled experiment to compare two different module-level SBFL approaches and validate the effectiveness of WFPG. According to our preliminary experiments, the results are promising.

key words: fault understanding, spectrum-based fault localization, method- and block-level debugging

1. Introduction

Spectrum-based fault localization (SBFL) has been shown to be a very practical and efficient strategy, which uses instrumentation with a low computational overhead and a good scalability to produce good results in large codebases [1]. In this field, researchers have been mainly focused on proposing new techniques and investigating their performance without considering human factors [2], [3]. Some studies show that two factors, accuracy and fault understanding, mainly affect the usefulness of SBFL techniques [3], [4], [6].

Lucia et al. [5] observed that many real-life bugs span across multiple lines. Parnin and Orso pointed out that “perfect bug detection” is generally unrealistic [6]. Therefore, giving a suspicious statement to directly localize the root cause of failures is unrealistic. Generally, module design should enforce adherence to the principle of high cohesion and low coupling, and a control flow graph for a module could easily aid programmers in performing program understanding. Therefore, in this work, we propose a novel SBFL framework, which includes the following two phases: localizing module-level fault based on SBFL and visualizing a weighted fault propagation graph (WFPG) for a hypothesis fault module to be checked. The two main factors that influence the effectiveness of the proposed approach include (1) accurate module-level fault localization and (2) effective WFPG.

Considering the cost of fault localization, here, we only focus on SBFL techniques. Those heavy-weight fault localization techniques, such as [8], are also easily integrated into the proposed fault localization framework. For those SBFL techniques, selecting the best profiling type and granularity level is problematic when SBFL comes to operationalization in industry [9], which is mainly factor to affect accuracy for module-level fault localization. In our framework, programmers use the node weighted information to perform a search-based fault localization and understand the program through WFPG. It is difficult to directly compare the two techniques. We turn the research question of effective WFPG into answering whether WFPG is more effective than SBFL to improve block-level fault absolute ranking. Therefore, an empirical study was conducted to answer the following two main research questions:

• RQ1: What is the best profiling type and granularity level to locate module-level faults using SBFL techniques?
• RQ2: Will WFPG effectively improve block-level fault absolute ranking?

2. Our Approach

2.1 Module-Level Fault Localization

We propose two approaches to localize potential fault modules based on module-hit (called SFL-m) and block-hit (called SFL-b). The two hit spectra can be mapped as Coverage Matrix A, which is a binary \( N \times M \) matrix, where \( N \) indicates the number of successful/failed executions, and \( M \) indicates the number of the instrumented program entities of the buggy program. The result of each execution can be viewed as N-length Result Vector \( e \), in which ‘0’ indicates successful, and ‘1’ indicates failed. The pair \( (A, e) \) serves as an input for SBFL. The coverage matrix and result vector...
are shown in Fig. 1.

Note that the quantities in the right of Fig. 1 have been annotated with fault localization-specific terms, which can be used directly to calculate the suspiciousness score for each program entity. For program entity \( j \), \( N_{\text{PQ}} \) is defined as:

\[
N_{\text{PQ}}(j) = |\{i | a_{ij} = P \land e_i = Q\}|
\]

(1)

where \( N_{\text{PQ}} \) is the number of runs in which the entity \( j \) has been covered during execution (‘C’) or not covered during execution (‘U’), and where the runs failed (‘F’) or successful (‘S’). For instance, \( N_{\text{CF}} \) counts the number of times program entity \( j \) has been covered in failed executions. Those suspicious metrics are all defined based on the four values \( N_{\text{CF}}, N_{\text{UF}}, N_{\text{CS}}, \) and \( N_{\text{US}} \) for each program entity. In this paper, we choose \( \text{Dstar} \), which is a commonly chosen suspicious metric. The formula of \( \text{Dstar} \) is shown as Formula (2), which is detailed in [1].

\[
S_{\text{Dstar}}(j) = \frac{(n_{\text{CF}}(j))^\dagger}{n_{\text{UF}}(j) + n_{\text{CS}}(j)}
\]

(2)

For SFL-m, we can choose a metric to calculate suspiciousness for modules directly. However, we cannot measure the suspiciousness based on SFL-b directly. Similar to [14], for SFL-b, we use the block suspiciousness scores to generate the suspiciousness. The idea behind this is that because a fault block is contained by its module, the higher the maximum of the block suspiciousness score in a module is, the higher the module suspiciousness score. We formally define this concept as Formula (3):

\[
S(M_i) = \max\{S(b_j) | b_j \in M_i\}
\]

(3)

In Formula (3), \( S(M_i) \) is the suspiciousness score for module \( M_i \), and \( S(b_j) \) is the suspiciousness score for block \( b_j \) contained by \( M_i \).

### 2.2 Weighted Fault Propagation Graph

For a hypothesis fault module \( m_i \), a weighted fault propagation graph (WFPG) is defined as \( \text{WFPG}(N, E, W_N, E_X, m_i) \), where \( N \) and \( E \) are the set of nodes and edges, respectively. \( W_N \) is weighted information about a node \( N \), \( W_E \) is weighted information about an edge \( E \), and \( m_i \) is a hypothesis fault module that a programmer wants to verify.

It is generally known that a fault within a basic block may propagate a series of infected program states before it manifests a failure. That is to say, even if every failed run covers a basic block, the basic block is not necessarily the root cause of failures. Inspired by [12], for an edge \( e_i \), the higher the suspiciousness score is, the more suspicious the propagation of program states, and the more suspicious the propagation of the program state by \( e_i \) is deemed to be. Therefore, we can generate a WFPG to express fault propagation based on this idea.

We first calculate the weighted information for edges using Formula (4), where \( N_{\text{CF}} \) is the number of edge \(<b_j, b_k>\) covered in failed runs, \( N_{\text{CS}} \) is the number of edge \(<b_j, b_k>\) covered in passed runs, and \( N_{\text{F}} \) and \( N_{\text{S}} \) are the number of failed runs and passed runs, respectively. The intuition is that weighted information for an edge is proportional to the number of failed executions and inversely proportional to the number of passed executions that covered it. After executing block \( b_i \), the execution may transfer control to one of its successor blocks. Suppose \( b_k \) is a successor block of \( b_i \). The program states of \( b_i \) may be propagated to \( b_k \) by edge \(<b_i, b_k>\). We approximate the expected number of infected program states of \( b_i \) observed at \( b_k \) as the fraction of the suspiciousness score of \( b_i \) from that of \( b_k \). Therefore, we use Formula (5) to model the portion of the contribution of edge \(<b_i, b_k>\) with respect to the total contribution by all incoming edges of \( b_k \). In general, a block \( b_j \) may have any number of successor blocks. Therefore, we sum those fractions from every successor block of \( b_j \) to generate weight information of node \( b_j \). The weighted score of node \( b_j \) is defined as Formula (6).

\[
W_{\text{edge}}(b_i, b_j) = \frac{N_{\text{CF}}}{N_{\text{F}}} - \frac{N_{\text{CS}}}{N_{\text{S}}}
\]

(4)

\[
C(b_i, b_k) = \frac{W_{\text{edge}}(b_i, b_k)}{\sum_{\text{edge}(*, b_k)} W_{\text{edge}}(*, b_k)}
\]

(5)

\[
W_{\text{node}}(b_j) = \sum_{\text{edge}(b_k)} [W_{\text{node}}(b_k) \cdot C(b_i, b_k)]
\]

(6)

We normally calculate a block suspiciousness score via its successor blocks. However, a module also has some exit nodes such as statement \( \text{return} \), \( \text{exit} \), etc. Those nodes have no successor blocks in the interprocedural. Thus, Formula (6) cannot be used to calculate the weighted information. In this way, Formula (7) is used to calculate the weighted information.

\[
W_{\text{node}}(b_j) = \sum_{\text{edge}(b_k)} [W_{\text{edge}}(*, b_j)]
\]

(7)

We construct an equation set for all nodes and solve the equations to generate weighted information for each node. Considering that some weighted values are negative, these values are mapped to \([0, 1]\) in order to easily visualize the results.

### 3. Experiment

In our experiment, three Siemens programs, \textit{print\_tokens2}, \textit{...}
replace, and schedule, containing more modules, are used to evaluate the effectiveness of the proposed approach. Table 1 shows the characteristics of those programs.

### 3.1 Answer RQ1

In order to answer RQ1, we perform an experiment to compare SFL-b with SFL-m in terms of effectiveness. We choose Dstar [1], one popular SBFL, as the baseline. According to recent work by Xia et al. [4], programmers inspect the first several program entities outputted by a fault localization tool in sequence. Therefore, we use absolute ranking to evaluate the proposed fault module localization approach. For example, an absolute ranking range of top3-5 implies the root faulty module ranked at top 3 to top 5 position in the fault ranking list. We give the number of program versions in the absolute ranking range to compare the two approaches.

Table 2 shows the result of the study. The number and percentage columns show the number of buggy program versions ranked in the range of absolute ranking, and its percentage for SFL-b and SFL-m. For example, SFL-b ranks 9 root faulty modules at the top, and its percentage is 20.5%; SFL-m ranks 12 root faulty modules at the top, and its percentage is 27.3%. In this case, SFL-m outperforms SFL-b. However, the number of SFL-b ranked at top 1-3 and top 1-5 by far exceeded the results of SFL-m. We conjectured that this result is because the module-hit program spectrum is coarse-grained, which would not reflect the Fault&Failure model of the fault. That is to say, SFL-b is effective to localize module-level faults. We could suppose the approach is effective if root cause is ranked in top k (k could be set as 3). Therefore, as a whole, SFL-b is better than SFL-m. The result may inspire future study on module-level fault localization based on SBFL techniques.

### 3.2 Answer RQ2

To answer RQ2, the node weighted information of WFPG was used as the suspiciousness score to generate a fault ranking list and observe whether the weighted information can further improve the fault absolute ranking. The fault ranking list was generated based on WFPG, called WFPG-w. To do this, Dstar and WFPG-w are run to generate a block-level fault ranking list. An improvement metric was used to estimate the approach improvement [10]. The improvement metric is defined as Formula (8).

\[
\text{Impr}^{SBFL}(A, B) = \begin{cases} 
0, & \text{if } B = 0 \text{ and } A = 0 \\
-100\% & \text{if } B = 0 \text{ and } A > 0 \\
\frac{B - A}{B} \times 100\%, & \text{Otherwise}
\end{cases} \quad (8)
\]

Figure 2 shows the results of the study. There exist 11 fault versions ranked in the top 1 in the 44 fault versions. Those program versions cannot be further improved; thus, they are ignored. The results show that the proposed approach improved over the Dstar for 26 versions and performs the same as Dstar for 7 versions, which indicates an effectiveness rate of 75.8%. The results show that no fault versions perform worse than Dstar. Therefore, the weighted information of WFPG is effective to guide programmers to localize block-level faults in practice. In those 26 versions, the average improvement is 59.6%, and it is worth mentioning that 6 root faults were ranked at the top of the fault ranking list.

### 3.3 Experimental Limitations

The major limitation about the experiments is whether the technique can scale to large real programs. In the preliminary experiments, we use a subset of the Siniens Programs. As well as existing most experiments in fault localization community, those programs are all small programs contained artificial faults, which are generated either by mutation tools or manually [15]. Therefore, the result of preliminary experiments only gives indications that the technique can be useful.

### 4. Related Works

Various approaches already exist to locate module-level faults. For instance, Shu [8] proposed and evaluated a novel method-level statistical fault localization technique, called MFL, which is based on causal inference. However, those techniques are all heavy-weight fault localization tech-
niques. Considering the cost of fault localization, we focus on SBFL techniques for method-level faults. In [14], De Souza et al. provided a search roadmap for code hierarchy (CH) and integration coverage-based debugging (ICD) techniques, which can guide a programmer toward faults. In order to aid programmers in understanding software, many graph models were proposed including WSDG [7] and PPDG [11]. In [13], Gouveia et al. proposed three dynamic graphical forms using HTML5 to display the diagnostic reports yielded by SBFL. Different from their work, the proposed WFPG is a fault weighted propagation graph based on control flow graph, which is commonly used for programmers in the software community. The proposed WFPG is a graph for a specific hypothesis fault module, which is better understood by programmers.

5. Conclusion and Future Works

In this paper, a SBFL framework is proposed to expedite software debugging. Compared with previous studies, the proposed approach locates bugs through two-level fault localization, which reduces interference between the mechanism of SBFL and the actual assistance needed by programmers in debugging.

As future work, we plan to investigate more empirical studies to further evaluate the effectiveness of our approach in large real programs. We would also like to build an oracle that can predict the effectiveness of a module-level fault localization technique using SBFL. Based on the result, we can perform our framework effectively if the module-level SBFL is effective for a buggy program.

Acknowledgments

This work was supported by the Anhui University Natural Science Fund Key Project (Grant Nos. KJ2018A0116, KJ2016A252, and KJ2017A104), the National Key Research and Development Program (Grant No. 2016YFB100), Project 61772270, 61562087 supported by NSFC of China, the Anhui Natural Science Foundation (Grant No. 1608085MF147), and the Safety-Critical Software Key Laboratory Research Program (Grant No. NJ2018014).

References

[1] W.E. Wong, R. Gao, Y. Li, R. Abreu, and F. Wotawa, “A survey on software fault localization,” IEEE Trans. Softw. Eng., vol.42, no.8, pp.707–740, 2016.
[2] R. Minelli, A. Mocci, M. Lanza, and T. Kobayashi, “Quantifying program comprehension with interaction data,” 14th International Conference on Quality Software (QSIC), pp.276–285, IEEE, 2014.
[3] X. Xie, Z. Liu, S. Song, Z. Chen, J. Xuan, and B. Xu, “Revisit of automatic debugging via human focus-tracking analysis,” ICSE2016, pp.808–819, 2016.
[4] X. Xia, L. Bao, D. Lo, and S. Li, “Automated Debugging Considered Harmful” considered harmful: A user study revisiting the usefulness of spectra-based fault localization techniques with professionals using real bugs from large systems,” ICSME, pp.267–278, 2016.
[5] Lucia, F. Thung, D. Lo, and L. Jiang, “Are faults localizable?,” MSR2012, pp.74–77, 2012.
[6] C. Parnin and A. Orso, “Are automated debugging techniques actually helping programmers?,” ISSTA, pp.199–209, 2011.
[7] F. Deng and J.A. Jones, “Weighted system dependence graph,” ICST2012, pp.380–389, 2012.
[8] G. Shu, B. Sun, A. Podgurski, and F. Cao, “MFL: Method-level fault localization with causal inference,” ICST, pp.124–133, IEEE, 2013.
[9] M. Golagha and A. Pretschner, “Challenges of operationalizing spectrum-based fault localization from a data-centric perspective,” Proc. Software Testing, Verification and Validation Workshops (ICSTW), pp.379–381, IEEE, 2017.
[10] Y. Wang, Z. Huang, Y. Li, and B. Fang, “Lightweight fault localization combined with fault context to improve fault absolute rank,” Science China Information Sciences, vol.60, no.9, 092113, 2017.
[11] G.K. Baah, A. Podgurski, and M.J. Harrold, “The probabilistic program dependence graph and its application to fault diagnosis,” IEEE Trans. Softw. Eng., vol.36, no.4, pp.528–545, 2010.
[12] Z. Zhang, W.K. Chan, T.H. Tse, B. Jiang, and X. Wang, “Capturing propagation of infected program states,” Proc. ACM SIGSOFT Symposium on the Foundations of Software Engineering, pp.43–52, ACM, 2009.
[13] C. Gouveia, J. Campos, and R. Abreu, “Using HTML5 visualizations in software fault localization,” 2013 First IEEE Working Conference on Software Visualization (VISSOFT), pp.43–52, IEEE, 2013.
[14] H.A. de Souza, D. Mutti, M.L. Chaim, and F. Kon, “Contextualizing spectrum-based fault localization,” Information and Software Technology, vol.94, pp.245–261, 2018.
[15] S. Pearson, J. Campos, R. Just, G. Fraser, R. Abreu, M.D. Ernst, D. Pang, and B. Keller, “Evaluating and improving fault localization,” Proc. 39th International Conference on Software Engineering, pp.609–620, IEEE Press, 2017.