

- 阅读论文,准备报告

- 1. 《动态 Web应用中的缺陷定位研究》 —— WDL方法
- 2. 《一种基于遗传算法的多缺陷定位方法》 —— GAMFal方法
- 3. 《MSFL: A Model for Fault Localization Using Mutation-Spectra Technique》——将mutation和 spectrum结合
- 4. 《A Hybrid Approach to Fine-grained Automated Fault Localization》 —— 提出了一种基于动态谱和静态谱的混合细粒度AFL方法。
- 5. 《Enhancing Spectrum-Based Fault Localization Using Fault Influence Propagation》——集成了基于频谱的故障定位和故障影响传播分析



A Hybrid Approach to Fine-grained Automated Fault Localization

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PART 03 How does it perform?



Why use HybridAFL?







Challenging

Tedious

Time-consuming

Automated

Simple

Intuitive









What is HybridAFL?

Rationale: Some types of statements are significantly more/less error-prone than others, and thus statement types could be exploited for fault localization.

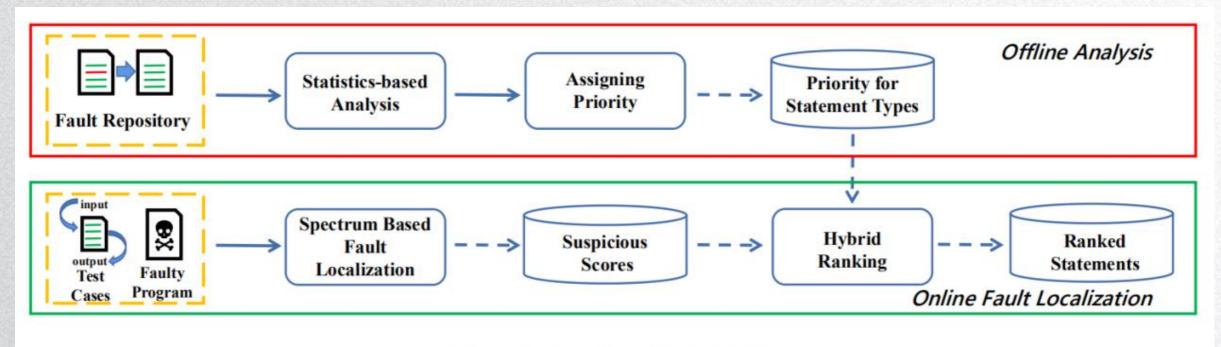
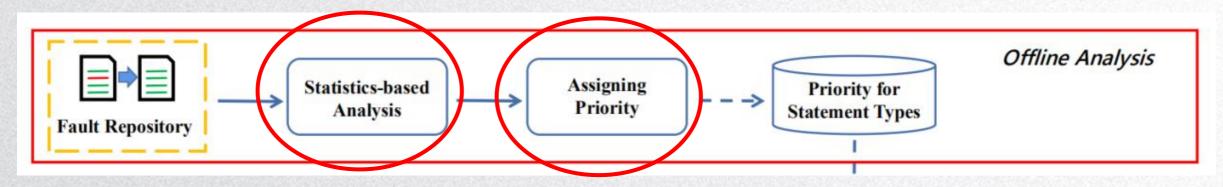


Figure 1: Overview of HybridAFL

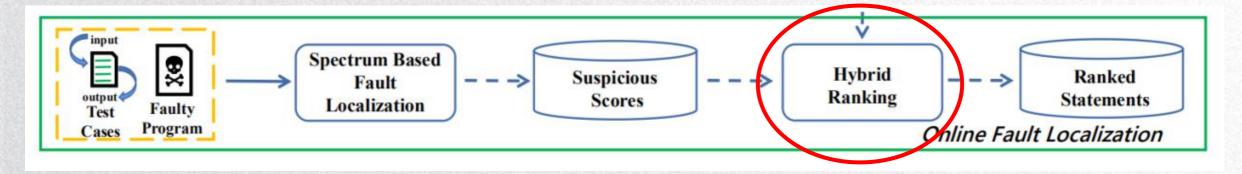
What is HybridAFL?



- HybridAFL applies statistics analysis to a fault repository to compute the error-proneness for each of the statement types involved in the repository.
- Based on the resulting error-proneness, HybridAFL identifies special statement types that are steadily more/less error-prone than others.
- HybridAFL assigns priorities to special statement types selected in the preceding step. The more error-prone a statement type is, the greater priority it receives.



What is HybridAFL?



- For a faulty program to be debugged, HybridAFL collects suspicious statements from the faulty program and computes their suspicious scores by traditional SBFL.
- HybridAFL adjusts the suspicious scores according to statement types, i.e., multiplying the SBFL suspicious scores by the priorities assigned to the statement types.
- All of the suspicious statements are ranked by the updated suspicious scores in descending order. Statements on the top are more likely to be faulty and thus should be inspected first.

2.1 Statistics-based Analysis on Fault Repositories

Key Rational: Different types of statements are not equally error-prone.

$$TSS(pr_i) = \bigcup_{k=1}^{TV(pr_i)} SS(V_{i,k})$$

$$TFS(pr_i) = \bigcup_{k=1}^{TV(pr_i)} FS(V_{i,k})$$

$$AP(pr_i) = \frac{|TFS(pr_i)|}{|TSS(pr_i)|}$$

$$TSS(pr_i) = \bigcup_{k=1}^{N} TSS(pr_i, t_j)$$

$$TFS(pr_i) = \bigcup_{k=1}^{N} TFS(pr_i, t_j)$$

$$AP(pr_i, t_j) = \frac{|TFS(pr_i, t_j)|}{|TSS(pr_i, t_j)|}$$

2.2 Assigning Priorities to Special Statements

Key Rational: Some types of suspicious statements are significantly more/less error-prone than others.

1)
$$RP(pr_i, t_j) = AP(pr_i, t_j)/AP(pr_i)$$

 $RP(t_j) = \{RP(pr_1, t_j), RP(pr_2, t_j), \dots, RP(pr_n, t_j)\}$

nor_
$$RP(t_j) = \{lg(RP(pr_1, t_j)), \dots, lg(RP(pr_n, t_j))\}$$

3)
$$W(t_j) = lg^{-1}avg(nor_RP(t_j))$$
$$= 10^{avg(nor_RP(t_j))}$$

2.3 Hybrid Ranking

Key Rational: Different types of statements are not equally error-prone.

$$sus'(ss_j) = sus(ss_j) \times W(T(ss_j))$$

How	Evaluation
RQ01	Are different types of statements equally error-prone?
RQ02	Does the proposed approach outperform the state-of-the-art fine-grained fault localization techniques?
RQ03	How does the performance of the proposed approach varyin locating different types of faulty statements?
RQ04	Can we further improve the proposed approach by assigning priorities to all statements besides the special statementsselected in Section 3.3?
RQ05	Can we further improve the proposed approach by leveraging the median instead of the average in Formula 17?
RQ06	Should we apply multi-level sorting to fault localization byleveraging both SBFL scores and priorities of statement types?

Can we improve other SBFL algorithms in the same wayas we improve Ochiai?

RQ07

RQ1: Some Types of Statements are Significantly More Error-Prone

Than Others

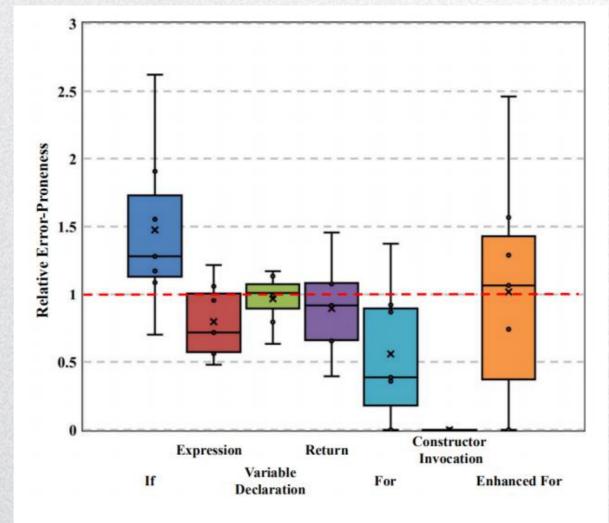


Figure 2: Relative Error-Proneness Varying among Programs

RQ2: HybridAFL Improves the State of the Art

Table 3: Absolute Waste Effort (AWE)

Approaches Projects	Math	Closure	Lang	Cli	JSoup	Databind	Compress	Overall
Ochiai (x)	7,227	41,306	1,220	1,260	3,468	7,327	2,425	64,223
HybridAFL (y)	5,524	37,448	907	1,103	3,786	7,445	2,066	58,279
Relative Reduction $(1 - y/x)$	23.6%	9.3%	25.7%	12.5%	-9.2%	-1.6%	14.8%	9.3%

RQ3: Good at Locating High-Priority Statements

Table 4: Effect on Different Types of Statements

	If	Variable Declaration	Return	Expression	For	Constructor Invocation	Others
Priorities	1.36	1	1	0.75	0.4	0	1
#Improved Cases (x)	66	15	20	1	0	0	6
#Decreased Cases(y)	0	11	19	50	3	0	0
#Draw Cases(z)	3	4	6	22	0	0	5
Chance of Improvement $(x/(x+y+z))$	95.7%	50.0%	44.4%	1.4%	0%	2 %	54.5%
Chance of Reduction $(y/(x+y+z))$	0%	36.7%	42.2%	68.5%	100%	H 2	45.5%



RQ4: Selection of Special Statement Types

Table 5: Selection of Special Statement Types Reduces AWE

Programs Setting	Math	Closure	Lang	Cli	JSoup	Databind	Compress	Overall
Selection Enabled (x)	5,524	37,448	907	1,103	3,786	7,445	2,066	58,279
Selection Disabled (y)	6,420	36,933	1,140	1,108	3,917	8,240	2,003	59,643
Relative Reduction in AWE $(1 - y/x)$	-16.2%	1.4%	-25.7%	-0.5%	-3.5%	-10.7%	3.0%	-2.3%



RQ5: Average VS. Median

Table 6: Derivation of Priorities Has Minor Effect on AWE

Projects Priorities	Math	Closure	Lang	Cli	JSoup	Databind	Compress	Overall
Average (x)	5,524	37,448	907	1,103	3,786	7,445	2,066	58,279
Median (y)	5,666	37,523	986	1,131	3,648	7,585	2,047	58,586
Relative Reduction in AWE $(1 - y/x)$	-2.6%	-0.2%	-8.7%	-2.5%	3.6%	-1.9%	-0.9%	-0.53%



RQ6: Multi-level Sorting Does Not Work

Table 7: Multi-level Sorting Increases AWE

Projects Sorting	Math	Closure	Lang	Cli	JSoup	Databind	Compress	Overall
Hybrid	5,524	37,448	907	1,103	3,786	7,445	2,066	58,279
Multi-Level (SBFL First)	6,716	39,762	1,177	1,196	3,385	7,357	2,238	61,931
SBFL Only	7,227	41,306	1,220	1,260	3,468	7,327	2,425	64,223
Multi-Level (Priority First)	4,701	52,101	1,068	1,518	9,965	36,144	2,419	107,916
Priority Only	6,459	77,752	1,267	1,965	13,405	53,571	2,938	157,357



RQ7: Improving Various SBFL Algorithms

Table 8: Relative Improvement on Various SBFL Algorithms

SBFL Algorithms Projects	Math	Closure	Lang	Cli	JSoup	Databind	Compress	Overall
Ochiai	23.6%	9.3%	25.7%	12.5%	-9.2%	-1.6%	14.8%	9.3%
Jaccard	14.3%	9.9%	5.9%	8.5%	-9.2%	4.6%	15.0%	8.8 %
DStar	15.3%	10.1%	14.0%	8.1%	-9.2%	3.4%	12.2%	9.0 %
Barinel	14.3%	9.9%	9.0%	8.4%	-9.2%	7.2%	15.1%	9.2%

THANK YOU FOR YOUR LISTENING.

谢谢您的聆听