Fix Director for Automated Program Repair

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***Abstract*—As the scale of software increases, automated program repair (APR) is required as an essential technology to reduce bug-fixing manual effort. One of the most effective APR approaches is the template-based APR. Although this data-driven approach has made many improvements in fixing bugs, there is still a lack of information utilization at each stage of the program repair. In this paper, we propose a fix pattern prioritization APR technique. We do not just use the test cases to determine whether the source file is fault or not, but as a material for why the bug occurred. With this information, we select a more appropriate fix action and apply it first to increase the efficiency of the automated program repair.**

***Keywords*—Software engineering, Automated program repair, Fix pattern prioritization**

I. Introduction

The scale of modern software developments are growing. As a result, the tasks of maintaining and repairing software have been consuming more time and cost. Recent study showed that these process account for about 50% of the software development [1]. To reduce this excessive cost, the demand for system to automatically fix software defects has increased. In this aspect, various approaches of automated program repair techniques have been proposed. Most of them are search-based APR [2, 3, 4, 5, 6, 7, 8]. They generate patch candidates using predefined sets of mutation operators with fault space determined by Fault Localization (FL) techniques. And they search correct patch that passes all given test cases among generated patch candidates from APR techniques. Despite this novel approach, there are some problems. First, search space to generate correct patch is usually huge. Second problem is correct patches may not exist in the search space, so APR techniques cannot fix the program. In addition, even if we increase the search space to find the correct patch, we are not sure that we can find the correct patch. Rather, it can only cause an increases cost in time and effort. To solve this problem, other approaches have been proposed including template-based [9,10,11,12,13,14], machine learning-based [15,16,17,18], etc. In particular, template-based APR techniques have been evaluated as the most effective and superior performance techniques [19]. This approach is strategy of APR to generate concrete patches based on fix patterns (also referred to as fix templates) which are predefined using human written patches from open source repositories. Because these approaches leverage predefined template from human-written patches, we can find more correct patches and reduce the cost. Despite these efforts, APR systems still do not have enough effectiveness for the cost it puts in. For example, many techniques including template-based APR go through three steps to repair the program. First step is the fault localization (FL), which identifies the fault Location. The second step is to generate candidate patches based on the proposed approaches in various ways. Final step is the validation, which checks the candidate patch that passes all given test cases. In this process, information used at individual step is often used only at each step and discarded. Specifically, the occurrence of failed test cases is used to check whether the source code has defects, but the information of the failed test cases is rarely used when going through other repair process. This disconnection in utilizing information can be a critical loss for program repair. In this paper, we leverage the information of the failed test cases to overcome disconnection in utilizing collected information. Using information of the failed test cases, we can infer what is the cause making defects and find a basis for which fix pattern should be prioritized in proceeding program repair. And these processes achieve performance improvements that reduce the cost.

II. Background and Motivation

A. Template-based APR

Template-based APR techniques generate bug-fixing candidate patches automatically using fix patterns extracted from human written patches. Existing template-based APR

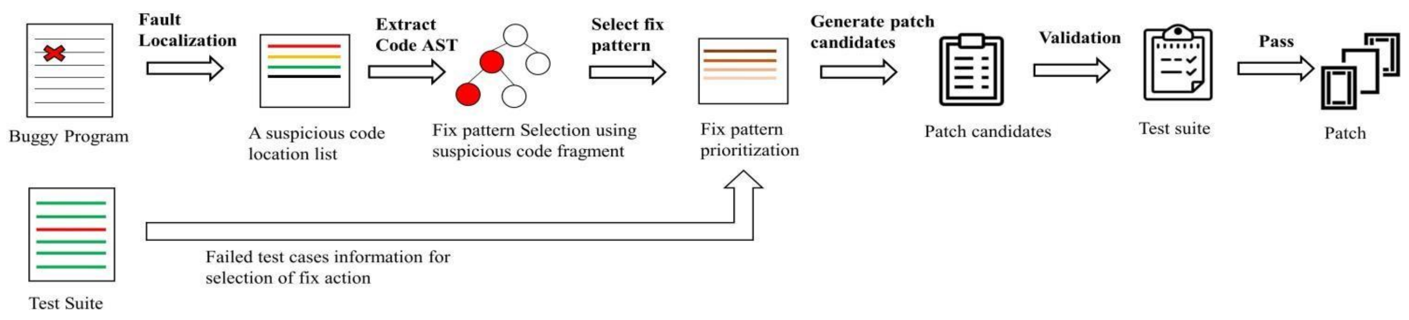
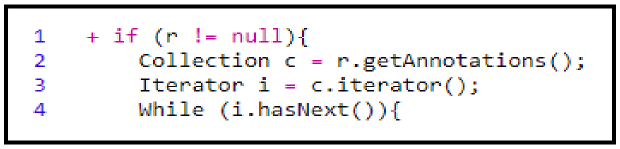

Fault Localization
Extract Code AST
Select fix pattern
Generate patch candidates
Validation
Pass
Buggy Program
A suspicious code location list
Fix pattern Selection using suspicious code fragment
Fix pattern prioritization
Patch candidates
Test suite
Patch
Test Suite
Failed test cases information for selection of fix action

Fig. 1. Workflow of Fix director

techniques have own method to extract fix pattern and fix pattern classification. The progress of the template-based APR techniques is as follows. Template-based APR first identifies fault locations (e.g., statements and expressions) and uses the fix patterns that researcher extracted before to generate patch candidates. Finally, validate the patch candidate checking generated patch passes all given test cases. This process reduces the cost and increase the possibility of finding the correct patch over traditional approaches, (i.e., search-based APR).

B. *Fix pattern selection*

Existing template-based techniques have own approaches to select the fix patterns. CAPGEN [14] uses the frequency information of fix pattern and similarity information for suspicious fault location. TBar [19] uses the child node information of the suspicious fault location to select fix pattern. Many template-based APR techniques including above techniques use their own approaches using fault statement information to select fix patterns. But there is little consideration as to why this statement is wrong. They mainly utilize information suspicious statement e.g., (structure, node type, variable name). On the other hand, in case of developers, if the fault location is identified in the code, they diagnose why the source code is wrong using given failure history. Using failure information, developers repair the program. If APR techniques are able to obtain and utilize information from the failed test cases, it will be easier to determine what fix action to take. Fig 2 shows a defect, Chart-4, in Defects4j [22] benchmark. Line 2 is given as the bug line, then APR tools fix this code using given code snippet`s information. Most template-based APR techniques modify the program using selected fix patterns without specifying which problems to fix. This leads to a significant waste of resources and time. However, if we use information about the NullPointerException error message generated from test suite, we can obtain the direction of fix action. This makes program repair process easier.



```
1   + if (r != null){
2       Collection c = r.getAnnotations();
3       Iterator i = c.iterator();
4       While (i.hasNext()){
```

Fig. 2. The faulty code from Chart-4

III. APPROACH

Figure 1 shows an overview workflow of our approach. Fault localization is the first step. It identifies suspicious code locations where we apply the fix action. In our experiment, we used the perfect localization which means fault statement line number is given to reduce the FL noise. When the fault localization step makes a list of suspicious location, we try to select the fix pattern extracted from human patch written. In this process we utilize two different pieces of information, first is the suspicious statement context information. We traverse each child node of the suspicious statement AST and try to match each node with fix pattern predefined. Multiple fix patterns can be generated for each suspicious statement. Since classifying fix patterns works are similar with classifying the behavior of developers who fix bugs, considerations for bug type needs to be given to determine which fix action is more appropriate. This work is implemented by preferentially applying a more appropriate fix pattern for the bug, utilizing the information from the collected failed test case error messages. In case of null pointer exception, fix patterns that are more relevant to null pointer should be applied first. In addition, we prioritize fix patterns that should be taken for eight error types, such as when the wrong value was calculated or when the wrong index was referenced. Then, we applied this approach to 52 bugs generated correct patches using TBar which is the most effective template-based APR tool. And we measure changes in the rank of fix pattern that generated the correct patch. Table 1 shows the rank without prioritization and with prioritization results. Each pattern generates at least one to dozens of candidate patches. These pattern prioritization tasks are designed to generate the correct candidate patches faster and follow the process of real developers fixing bugs. Because selecting fix patterns is the same process as choosing what kind of fix action developers take, utilizing error messages as a basis for selecting fix pattern can be reasonable decision making.

TABLE I. FIX PATTERN RANK

BugId	Pattern rank that first correct patch appear	
	Without prioritization	***With prioritization***
Chart_1	1	1
Chart_4	2	1
Chart_8	1	1
Chart_9	2	1
Chart_11	1	1
Chart_12	5	5
Chart_19	1	1
Chart_20	1	1
Chart_24	2	1
Chart_26	2	2
Closure_2	2	1
Closure_4	1	1
Closure_10	1	1
Closure_11	1	1
Closure_13	3	3
Closure_38	1	1
Closure_40	3	3
Closure_46	1	1
Closure_62	1	1
Closure_70	4	3
Closure_73	1	1
Closure_102	4	4
Closure_115	5	5
Closure_117	3	5
Lang_6	2	2
Lang_10	4	4
Lang_24	1	1
Lang_26	3	2
Lang_33	2	1
Lang_39	2	1
Lang_47	3	1
Lang_51	3	3
Lang_57	2	2
Lang_59	1	1
Math_4	2	1
Math_5	1	1
Math_11	2	2
Math_57	1	1
Math_58	1	1
Math_65	4	3
Math_70	1	1
Math_75	1	1
Math_77	1	1
Math_79	1	2
Math_82	1	1
Math_85	1	1
Math_89	4	1
Mockito_26	3	1
Mockito_29	1	1
Mockito_38	2	1
Chart_1	1	1
Chart_4	3	1

🟦 Indicates that prioritization improves the pattern ranking

🟥 Indicates that prioritization degrades the pattern ranking

IV. Evaluation

A. *Experiment Setup*

For evaluating our approach, we select the Defects4J dataset as the evaluation benchmark. This benchmark is a widely used dataset and recent state-of-the-art APR systems targeting Java program defects in automatic program repair field. Defects4j consists of six large projects and contains 395 bugs in total. To reduce fault localization noise, we implement an experiment with information about buggy statement location.

We implement experiments in two ways. First experiment is a reimplementation of TBar which is the best effective APR technique in the world. TBar defines 35 code change patterns and apply different patterns according to the context of the bug statements. Therefore, several fix patterns are applied to one defect. When fixing bugs, we record the rank of the pattern that generates correct patch. The second experiment is using information from the failed test cases. And we prioritize fix patterns more related with bugs. And then we record the pattern rank as in the first experiment.

B. *Rsearch Questions and Results*

RQ1. How effective is the fix pattern prioritization?

We implement two experiments. First experiment is without fix pattern prioritization and the other is with fix pattern prioritization. Table 1 shows the results of two cases. The pattern ranking means pattern`s rank that first correct patch is found. For example, rank 1 means that correct patch is found in the first applied fix pattern. 6 means that it fails for the 5 fix patterns applied and succeed with the 6th fix pattern. In case of 15 bugs, the ranking of patterns has improved. Since multiple candidate patches are created in a single fix pattern, the change in fix pattern ranking 1 may be more change in patch candidate ranking.

RQ2. Can failed test cases information be fix ingredients for APR?

We collect 8 failed message types. For each type of errors, we match appropriate fix patterns for error message types and apply them to prioritization process. This process is similar with developer`s bug fixing process when they manually fix bugs. Because developer checks the error information and choose their fix behavior using collected bug information. Using this approach, we can get performance improvements as seen in Table1. As a result, Information on what type of errors can be the basis for which fix action should be chosen.

RQ3. Failed test cases information covers all cases?

Error messages do not cover bugs in all cases. In actual codes, there are quite a few cases where only the Assertion message appears. Additionally, there are no information about the error appears. In these cases, we are not able to prioritize which fix action to take because we do not have the additional error information.

V. CONCLUSION

Template-based APR techniques based on fix patterns have been studied in various approaches to fix the bug program. Although template-based APR techniques have been known as the most effective approach, there is still a lack of information utilization between the entire processes. APR is still less efficient than developers fixing bugs manually. Because most APR technologies focus on bug location to fix the bugs without consideration as to why the bugs occur, we may miss important information to repair the program. To overcome this, we try to prioritize fix action based on why the bug occurred in this study. Using information for bugs, we can get correct patch earlier. In future APR studies, it is necessary to increase the efficiency by using information on the location of bug as well as information on why bugs occur.

VI. FUTURE WORK

We conduct fix pattern prioritization for eight error message types. However, there are more error messages that need to be classified. Because there are more various error messages in real code. In some cases, it is difficult to judge only by the information in the error message in determining what defects are present in the actual code. Therefore, we need additional information on what causes the bugs. Thus, future research will be conducted with the aim of complementing the above limitations.

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